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EVALUATION AND MODELING DAF FOR THE PORT HARDY WATER TREATMENT PLANT FOR ANN CONTROL

By

RASEL MAHBOOB HOSSAIN

A thesis submitted to the Faculty of Graduate Studies and Research in partial fulfillment of the requirements for the degree of **Master of Science**

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The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies and Research for acceptance, a thesis entitled **EVALUATION AND MODELING DAF FOR THE PORT HARDY WATER TREATMENT PLANT FOR ANN CONTROL** submitted by **RASEL M. HOSSAIN** in partial fulfillment of the requirements for the degree of **Master of Science** in **Environmental Engineering.**

DEDICATION

This work is dedicated to my mother Dr. Towhida Khanam, without whose support and encouragement I would have never reached this level of study, and to my wife Sheela and my daughter Diya who have been hopeful and patient throughout this journey.

ABSTRACT

The artificial neural network (ANN) technology is one of the most efficient modeling tools currently available in the water treatment industry that can handle the non-linear and complex relationships governed by numerous physical, chemical and operational parameters of treatment processes. ANN modeling techniques were applied to evaluate the performance of the full-scale, pilot-scale, and bench-scale dissolved air flotation (DAF) treating low turbidity, low alkalinity and color water at Port Hardy, BC. The developed ANN models were able to predict DAF effluent color and DAF effluent turbidity with high degree of accuracy and holds promise for successful process control applications. Moreover, model built from a series of data generated even from a bench-scale study may be useful for successful process control of the DAF treatment plant in full-scale operation.

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LIST OF SYMBOLS AND ABBREVIATIONS

^{o}C	degrees celcius
%	percent
µm	micro meter
#/mL	number per milliliter
ANN	artificial neural network
ANOVA	analysis of variance
BAT	best available technology
$CaCO_3$	calcium carbonate
cm	centimetre
DAF	dissolved air flotation
DOC	dissolved organic carbon
DI	deionized water
gpm	gallon per minute
G	mean velocity gradient
HA	humic acid
HLN	hidden layer neurons

KPa	kilo pascal
KNN	Kohonen neural network
L	litre
LIR	Lennox Institute of Research
L/min	liter per minute
m^3/hr	cubic meters per hour
ML/D	megaliters per day
MGD	mega gallon per day
MLP	multilayer perceptron network
mg/L	milligram per litre
m/hr	meter per hour
mL/g	millilitre per gram
mL/min	millilitre per minute
min	minute
m^3	cubic meters
mm	millimetre
MAE	mean absolute error
Min	minimum
Max	maximum
NTU	nephelemetric turbidity unit

NOM	natural organic matter
NPTOC	non-purgeable total organic carbon
NRB	Newton Research Building.
PAC	polyaluminum chloride
PAHS	polyaluminum hydroxysulfate
Psi	per square inch
PSDs	particle size distributions
pt-Co	platinum cobalt
PHWTP	Port Hardy Water Treatment Plant
Q_{sat}	volumetric flow rate of saturated water
Q_{water}	volumetric flow rate of DAF influent water
Q_{flocc}	volumetric flow rate of flocculated water
Q_{total}	sum of Q_{sat} and Q_{water}
rpm	revolution per minute
R^2	coefficient of multiple regressions
R_R	recycle ratio, ratio of Q_{sat} divided by Q_{water}
s^{-1}	per second
SCADA	supervisory control and data acquisition
SOFMs	self-organizing feature maps

TCU	true colour unit
THMs	trihalomethanes
USA	The United States of America
UK	The United Kingdom
WRC	Water Research Center
WTP	water treatment plant

1 INTRODUCTION

The water treatment industry is striving to produce higher quality water due to the stringent regulatory guidelines for the removal of organic, biological, and other contaminants. This has caused the water treatment industry to look for reliable new technologies that could improve treatment process control. One such new technology is artificial neural networks (ANN). The ANN technology is one of the most powerful modeling tools currently available in the water treatment industry that can handle the nonlinear and complex relationships governed by numerous physical, chemical and operational parameters of drinking water treatment process. Moreover, the ANN can map the cause-effect relationships between the input and output parameters. This mapping of input-output relationships in the ANN model architecture allows developed models to predict output parameters with accuracy. The study described in this thesis involved the evaluation and modeling bench-scale, pilot-scale and full-scale dissolved air flotation (DAF) using artificial neural network technology.

1.1 Port Hardy Water Treatment Plant

EPCOR Water Services operates the Port Hardy Water Treatment Plant with a total capacity of 10 ML/D to serve a population of 6200, the largest community on the northern tip of Vancouver Island, British Columbia, Canada. The raw water source of the Port Hardy Water Treatment Plant is the Tsulquate River. The river drains Kains Lake, located about 12 kilometre upstream of Port Hardy and empties into the Hardy Bay. The

Tsulquate River watershed covers a 45 square kilometre area, and the watershed is undeveloped, forested and steeply sloped. The ground of the watershed is swampy and mossy which contributes to the distinctive high color (almost tea color), reported as tannic acid equivalents, of the water. The color of the Tsulquate River water is most likely a result of humic compounds transported to the lake from wetlands within the watershed and decomposition of vegetation. The naturally occurring organic acid, tannic acid possibly leaches from leaves and other organic material, giving the water a tea or coffee color. The water is not polluted but in its natural condition it has a low pH. Moreover, Tsulquate River provides a particular challenge to water treatment efforts due to its water quality (high color, low turbidity and low alkalinity); specifically the color is constantly changing, depending on the season and weather. The average turbidity varies from 0.4 NTU to 1.10 NTU, and the color varies from 30 TCU to 110 TCU, except during rainy days and winter storm events, when its fluctuation is very drastic. The poorest raw water quality is observed during winter storm events where color has gone up to 338 TCU and the turbidity has gone up to 19 NTU. The raw water temperature range is from 2°C to 14°C.

The raw water of Port Hardy Water Treatment Plant is highly color, low in turbidity, and low in alkalinity. Dissolved air flotation (DAF) is considered to be the best available technology (BAT) for the treatment of low turbidity, low alkalinity, highly color water (Bunker et al. 1995; Edzwald 1995; Krofta and Wang 1982; Rees et al. 1980; Steven et al 1995). A schematic diagram of Port Hardy Water Treatment Plant is presented in Figure 1-1. Raw water is pumped from the dam site into a flow splitter at the

treatment works. Alum and soda ash are rapidly mixed into raw water at this stage and the water is equally split into three trains of DAF treatment. Alum added to the raw water makes particles to form flocs and soda ash is used to supplement alkalinity for better hydrolysis in coagulation process. Particle destabilization occurs during the rapid mixing stage after the addition of coagulants, where the coagulants are dispersed uniformly and quickly so as to cause destabilization of colloidal particles. The particle flocculation and growth of aggregates occur during the slow mixing stage or flocculation stage. Floc particle densities are made less than water during this stage by attachment of saturated air bubbles to floc particles and are removed. The next stage is filtration, where the DAF effluent water is fed into four individual filters to further remove color and turbidity. The filtered water then flows by gravity to the clear well and is pumped to the reservoir. At this stage chlorine is added for microorganism reduction, and lime and CO_2 are added for pH control of the finished water. From the reservoirs, water flows by gravity to supply drinking water for the Town of Port Hardy.

1.2 DAF Performance at Port Hardy Water Treatment Plant

The Port Hardy Water Treatment Plant produces continuously good quality effluent water. However, during rainfall-runoff, the color of the raw water reaches very high values, and it becomes very difficult to operate the plant during these periods. The rapid change in color values makes it very difficult to keep the performance consistent. The plant operator finds it difficult to determine a good level of the soda ash and alum

doses to keep the plant performance steady. As a result the DAF effluent turbidity goes up, the DAF effluent particle count goes up and, as well, there is an increase in the filtered effluent turbidity and particle count, and the plant performance deteriorates easily.

It is desired to maintain the DAF effluent turbidity below 0.5 NTU all the time for better filter performance. Effluent turbidity higher than 0.5 NTU from DAF causes early filter breakthrough. Moreover, the plant operator also wants to maintain DAF clarifier pH in an optimum range; and DAF effluent color below 5 TCU during the low color periods (0 to 60 TCU), below 10 TCU during medium color periods (60 TCU to 100 TCU), and below 20 TCU during the high raw water color periods of the Tsulquate River.

Successful flotation performance of the Port Hardy Water Treatment Plant is dependent upon chemical treatment (pH, and dose). The pH of coagulation is the most important operating parameter for producing good removals of color and turbidity (Edzwald 1995). However, good removals of color and good maintenance of DAF effluent turbidity below 0.5 NTU were reported over a wide range of raw water conditions at the plant. On average, color removals greater than 90% were achieved at Port Hardy Water Treatment Plant after flotation.

The key issue for successful DAF at Port Hardy is to maintain a certain pH level in its clarifier. The operation of DAF treatment plant using alum and soda ash is extremely pH sensitive and this scenario made the plant operation more challenging. The

plant works well only if the DAF effluent pH could be maintained between 6.3 and 6.8. However, the favorable pH condition at the DAF clarifier was 6.5. During the reactions, alum acts as an acid to reduce the pH and alkalinity of the raw water. The insufficient alkalinity of raw water makes aluminum ions soluble rather than insoluble and they do not participate in the hydration and olation reactions necessary to make the alum effective as a coagulant (Edzwald 1995). On the other hand, application of too much soda ash raises the pH so that the aluminum ions become soluble, and the efficiency of coagulation is decreased. In these instances the plant experiences higher than normal finished water turbidity, higher particle count and much of the aluminum passes through in the filtered effluent water. Effluent water quality can only be maintained in Port Hardy Water Treatment Plant with good operational knowledge, experience of accurate alum dose and soda ash dose, and good engineering judgment.

Temperature affects the dominant mechanism and the efficiency of coagulants (alum) in Port Hardy Water Treatment Plant. Even though the effect of temperature on coagulation is not well understood, low temperature (below $4^{o}C$) inhibits the removal of color as well as removal of turbidity in the plant. High flow rate has an adverse impact on the effluent quality of DAF at Port Hardy. Turbidity and overall particle counts of the DAF effluent as well as the filtered effluent goes up during the higher plant flow. This could be due to the higher hydraulic loading rate that the DAF plant experiences and gives the coagulants and chemicals less reaction time, less detention time for flocculation and less time for successful flotation. However, the plant works better in the flow rate range between 120 m^3/hr to 230 m^3/hr.

1.3 Need for Automatic Control

The water treatment industry is striving to produce higher quality water at a lower cost due to stringent regulatory guidelines. Improved process control through the introduction of artificial neural network has increased the operational efficiency of chemical process plants in drinking water systems by reducing cost (Baxter et al. 2002b; Zhang and Stanley 1999). The coagulation process is one of the important stages in surface water treatment for successful removal of colloidal particles. However, the main difficulty related to successful operation is to determine the optimum coagulant dose related to the influent raw water quality. Good coagulation control as well as chemical dosing control is necessary for maintenance of satisfactorily treated water quality and operational cost. Traditional methods of controlling coagulant dose rely upon jar-test results and the experience of the operators. These practices make it difficult to cope quickly with a rapid fluctuation of raw water quality. Moreover, disadvantages associated with jar test are the necessity of performing the test manually, and the limitation to feedback control. To overcome these limitations, ANN is an excellent technology to evaluate non-linear relationships between the accumulated input and output numerical data. Thus, artificial neural networking technology can be a viable solution for better process control by optimizing coagulant and chemical dosages at Port Hardy Water Treatment Plant during rainfall runoff events or winter storm events. Moreover, once the ANN is trained with historical data, it can calculate results from a given input very quickly and has the potential to be used online in a control system.

1.4 Value of ANN for Control

The coagulation and flocculation processes in DAF involve many complex physical and chemical phenomena and it is very difficult to build a process control model using traditional methods. The extreme pH dependent nature of DAF, and the high variation of raw water color change during rainfall runoff and winter storm events make it even harder. Artificial neural network techniques are reliable for optimizing the process control in the treatment plant and one of the most interesting and practical tools for process modeling in complex situations (Zhang and Stanley 1999). An ANN is an important tool for identifying erroneous sensor measurements or unusual water characteristics. A recent study by Baxter et al. (2001a) puts neural networks close to the top of the list to be considered for process modeling in the drinking water treatment industry as promising research. Control experts have predicted the rapid development of this ANN technology (Han 1994).

1.5 Research Objectives

The research presented here is an evaluation of DAF in drinking water treatment at Port Hardy water at three different scales; as bench-scale, pilot-scale and full-scale. Also presented here is the artificial neural network modeling approach for DAF in drinking water treatment at Port Hardy. The objectives of this study are to: (1) evaluate bench-scale DAF for Port Hardy water treatment; (2) evaluate pilot-scale DAF for Port

Hardy water treatment; (3) evaluate Port Hardy DAF Treatment Plant; (4) develop ANN models for bench-scale, pilot-scale and full-scale DAF.

1.6 Organization of the Document

The remainder of this document is organized into seven sections: literature review, materials and method used in this research, ANN model development, discussion and evaluation, conclusions and recommendations, and references. The literature review will provide the background information necessary for understanding the research objectives. The literature review will mainly focus on humic water treatment using dissolved air flotation, coagulants and coagulant aids used for this type of water treatment, and the successful application of artificial neural networks in drinking water industry. The materials and methods section will mainly focus on the protocol used in bench-scale DAF operation as well as pilot operation; software and source of data used to build the ANN model; the ANN model building protocol; chemicals used during the research, etc. In the results and discussion sections, ANN model building approach at different stages from bench-scale, pilot-scale and full-scale DAF will be presented. An evaluation of DAF at three different scales (bench-scale, pilot-scale and full-scale) will be made from the model developed using ANN. The findings of the research will be presented in conclusions section in the document. The future research needs are presented in recommendations.

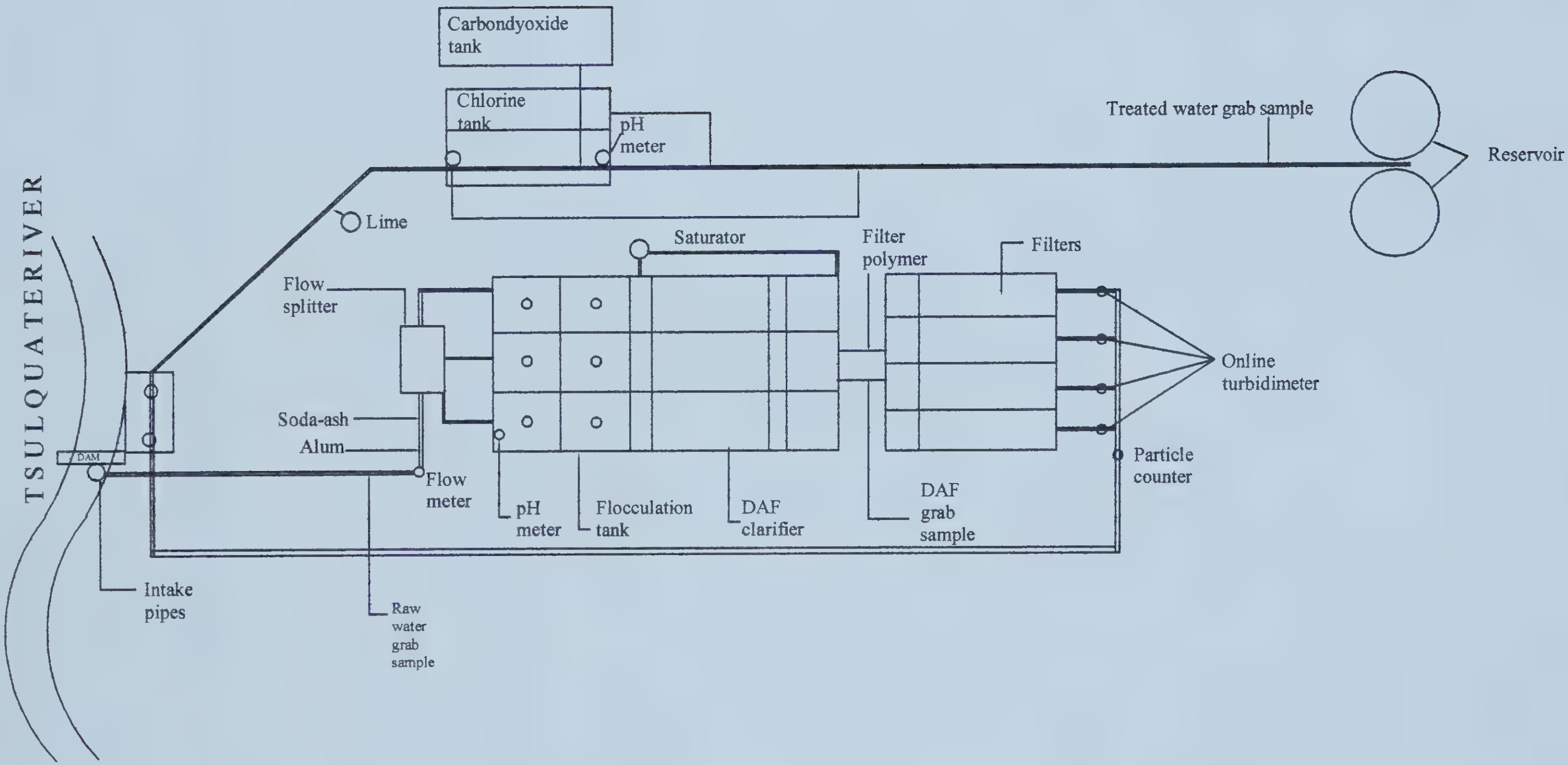

Figure 1.1 Schematic diagram of Port Hardy Water Treatment Plant

2 LITERATURE REVIEW

2.1 Colored Water Treatment

Utilities that formerly used only microorganism reduction (MOR) as a means of treating surface water supplies are now required to use filtration by the new guidelines for drinking water quality (Baxter et al.2001b). However, for certain water sources the application of filtration alone (direct filtration) has been shown to be either inefficient or ineffective treatment. These water types include low turbidity, low alkalinity, naturally colored, and algae laden waters. The coagulation of these waters produce low density particles that can cause filter clogging and premature breakthrough of particles in direct filtration plants. For these waters, the application of dissolved air flotation ahead of filtration has proven to be a beneficial alternative to sedimentation and a more reliable and efficient means of treatment (Janssens 1991; Edzwald 1995). Dissolved air flotation (DAF) removes these particles by forming bubble/particle aggregates, which rise to the surface of the flotation tank (Edzwald 1995). As mentioned earlier, the raw water quality of Port Hardy is low alkalinity, low turbidity and rich in humic substances or natural organic matter and DAF is the best available technology for treating this type of water.

2.1.1 Theoretical Concepts of Humic Water Treatment Using DAF

There are approximately 100 full-scale dissolved air flotation drinking water treatment plants currently operating in Scandinavia, the United Kingdom, Finland, the

Netherlands, and the United States dealing with low turbidity, low alkalinity, algae laden, colored water (Steven et al. 1995). The results of recent bench, pilot and full-scale applications have demonstrated that successful flotation performance relies upon properly destabilized particles, a sufficient flocculation period, and the introduction of sufficient air (Edzwald 1995; Steven et al.1995; Valade et al. 1996; Johnson et al.1995).

One of the basic fundamentals for successful flotation is that the flocs must be hydrophobic (Rees et al. 1980; Malley 1988; Edzwald et al. 1990; Janssens 1991). Bubble adhesion or attachment to particles requires hydrophobic particle surfaces or hydrophobic spots on the particles. Aluminum salts and iron salts are widely used as coagulants in the water treatment industry in North America (Edzwald 1995). Ferric and aluminum hydroxides produced during the coagulation process are hydrophilic, but, on the other hand, they can work well by destabilizing humic and other natural colloids and rendering the flocs suitable for successful flotation. The humic substances have the role of flotation collectors and make the flocs hydrophobic (Kitchener and Gochin 1981; Gochin and Solari 1983, Edzwald 1995). In this way, the natural circumstances promote the process desired by the engineers. Kitchener and Gochin (1981) have also verified experimentally and showed that a very low concentration of fatty acid soap (1.5 mg/L sodium oleate) promotes the flotation of flocs to a remarkable extent and thus making it possible for them to float.

Destabilization of particles is important for successful flotation as well as for sedimentation. Nevertheless, the floc size can be smaller and, consequently, low

coagulant doses can be used. The coagulant for DAF in treating low turbidity, low alkalinity and humic water is required for destabilization but not increasing the floc size (Edzwald et al. 1992). Destabilization means the compensation of the negative charge of the colloids, which is reducing the zeta potential (ZP). The air bubbles produced from the super-saturated water have negative charge (Tambo et al. 1985). Therefore, flocs with a positive charge or a zero charge can attract air bubbles better than negatively charged flocs. However, in practice, it is not necessary to strive for a complete neutralization of the charge as the flocculation process works well even with a slightly negative ZP (Swope 1977, Heinänen et al. 1995). The zeta potential of the flocs can be affected in two different ways. One such way is by increasing the coagulant dosage and the other way is by decreasing the pH (Hall and Packham 1965). Heinänen et al. (1995) tried to relate rising velocity and zeta potential as a function of pH for treating humic water. The DAF process gave the best results for treating low turbid and humic water, when the maximum rising velocity was achieved at optimum pH values (Heinänen et al. 1995). The residence time in the flocculator for successful flotation in treating humic water is between 20 to 30 minutes (Edzwald 1995). This relatively short residence time in the flotation plant can provide an advantage for quick start up of the process and steady performance in terms of treated water quality.

There is an effect of temperature on humic water treatment. High rising velocities usually result in a more efficient DAF process. Therefore, low temperatures have a negative effect on performance due to the viscosity-related lower rise velocity. Removal of color and especially low molar mass organic substances by coagulation seems to be

inhibited at low temperature (Knocke et al. 1986). Temperature effects may have various reasons. The increased viscosity of cold water may hinder coagulant dispersal or sedimentation (Amrithrajah and Melia 1990), may influence the kinetics and equilibrium of hydrolysis and metal precipitation (Knocke et al. 1986), and poorer removal may also result from the characteristics of the floc formed at low temperature (Morris and Knocke 1984).

2.2 Coagulants and Coagulant Aids Used for Colored Water Treatment

Dissolved air flotation (DAF) is used in place of conventional gravity settling as a means to separate low density floc particles from water (Zabel 1984). The results of DAF experiments using synthetic and natural waters showed that good DAF treatment requires good coagulation (Edzwald and Malley 1989). The removal of dissolved natural organic matter (NOM) requires coagulant addition to produce direct precipitation and adsorption of the NOM on precipitated metal hydroxide particles. Proper chemical pre-treatment is a means for removal of aquatic humic substances from solution and particle destabilization (AWWA 1999).

2.2.1 Removal of NOM

Organic matter has been associated with unpleasant taste and odour, potential transport of adsorbed hydrophobic organic and inorganic contaminants, growth substrates

for bacteria, increased coagulant and microorganism reduction chemicals demand and, more importantly, disinfection by-products (trihalomethanes as THMs) (Exall and Vanloon 2000; White 1997; Randtke 1988). The attention to the removal of organic matter from drinking water has increased in recent years. Natural organic matter is the largest source of organic material in raw water. It is comprised of both particulate and dissolved matter. Dissolved natural organic matter is defined as the fraction that passes through a 0.45 μm pore filter and usually comprises the largest portion of the natural organic matter (Exall and Vanloon 2000).

Natural organic matter is primarily composed of humic substances, such as humic acids, fulvic acids, and tannic acids that result from decomposition of terrestrial and aquatic biomass. However, it can contain a range of organic species and microorganism and their discharges (Randtke 1988). Its source materials determine the chemical nature, or structure of NOM in a drinking water supply and the biogeochemical processes that take place in the watershed (Aiken and Kotsaris 1995).

Humic substances are chemically complex molecules with acidic, aromatic, hydrophilic, and hydrophobic regions. The functional groups such as carboxylic, phenolic groups, ketonic, quinonoid and methoxyl groups are thought to influence their reactivity during treatment. It is the dissociation of the more acidic of these functional groups at neutral pH values of the natural water that results in the high stability of these molecules as negatively charged, dissolved or colloidal species (AWWA 1979).

Generally the higher molar mass fraction of organic matter is removed readily by coagulation. However, the lower molar mass organic matter increases coagulant demand and cannot be removed effectively (Collins et al. 1986). The type of organic matter is a factor in its removal efficiency during treatment. Functional groups influence the solubility of organic compounds, which affects removal by coagulation. Studies showed that hydrophobic organic matter is more easily removed than hydrophilic organic matter (White 1997). Tannic acid represents relatively hydrophilic compounds of medium molar mass. Recent studies have shown that humic acids were removed more easily than tannic acid. Consequently, tannic acid needs higher coagulant doses than humic acid during treatment (Exall and Vanloon 2000).

2.2.2 Coagulants and Coagulant Aid

Coagulants most commonly used in drinking water treatment in North America are aluminum salts and iron salts. However, alum (aluminum sulphate) is the most common of these (AWWA 1989). In treating waters containing aquatic humic, alum, ferric chloride and polyaluminum chloride are effective coagulants (Malley 1988). Cationic polymer, anionic polymer, and non-ionic polymer have all been used successfully in the drinking water industry for treating humic water (Edzwald 1995).

Aluminum and iron salts undergo metal ion hydrolysis reactions when added to water and form a number of monomeric and possibly polymeric species (Exall and Vanloon 2001; Edzwald 1995). The nature of species formed is dependent on the raw

water pH, alkalinity, temperature, coagulant concentration and presence of organic matter (Exall and Vanloon 2001; Edzwald 1995, Edzwald et al. 1992). Prehydrolysis of simple coagulants like alum or aluminum chloride are improved by addition of base in cold water but may hinder organic matter removal at warm temperatures to some extent (Exall and Vanloon 2001; Edzwald 1995, Edzwald and Malley, 1989).

Bunker et al. (1995) studied pre-treatment considerations of coagulant selection for two different water supply types, aquatic humic and non-aquatic humic waters of low turbidity. They found alum, ferric salts, and various polyaluminum chloride (PACl) with different chemical properties were all effective in DAF when used under favorable conditions of dosage, pH, and flocculation time.

Flotation performance is often poorer when alum is used in treating cold waters of low turbidity and low DOC. Addition of high molecular weight polymers can improve flotation performance when alum is used to treat these latter types of waters, but not necessarily to aid floc particle-bubble attachment in DAF treatment of drinking waters (Zabel 1984; Edzwald and Malley 1989). Ferric chloride coagulant required four times the mass dosage (mg Fe/mg DOC) as that of the aluminum coagulants (Bunker et al. 1995). Bunker et al. (1995) also showed that alum yielded high turbidity compared to the other coagulants in treating Schoolhouse Lake, a high quality water supply of low turbidity and high aquatic humic matter and natural color. These data support the premise that alum floc particles may not attach effectively to bubbles at the zero point charge due to hydrophilic effects, and the effect increases in cold water. However, both PACl and

ferric chloride produced low turbidity near 1 NTU or less. Moreover, the problem with alum of producing hydrophilic floc causing poor bubble-floc attachment was rectified with the addition of high molecular weight polymers to hydrophobic particles. Bunker et al. (1995) in their studies also found that alum was slower to react than the PACl in cold waters and that it may require a longer flocculation times when treating aquatic humic type waters. Sulfate based PACl were effective in treating cold waters at short flocculation times of 2.5 to 5 minutes.

In treating waters low in particles and aquatic humics with alum, high molecular weight polymers may improve particle-bubble attachment and thus, increase the flotation performance. Studies by Edzwald et al. (1992) found that a small dose of an anionic polymer added 5 minutes after alum improved turbidity removal and required only 2.5 minutes of flocculation after polymer addition. The polymer concentration needed to improve floc separation was very low (0.001 mg/L) and the turbidity without polymer addition was greater than 1 NTU. This study was done at bench scale using an Aztec Jar test unit at 4°C using Wachusett reservoir water (high color, low turbidity), Boston, Massachusetts, USA. Previous research at the bench scale made the case that when treating waters of low turbidity and DOC, amorphous $Al(OH)_3$ particles may not attach effectively to the bubbles at the zero point of charge due to hydrophilic effects (Edzwald et al. 1990). The anionic polymer could make the $Al(OH)_3$ particles hydrophobic and have sufficient size to extend from the $Al(OH)_3$ surface into solution for distances larger than the bound water layer thickness and attach to other particles or bubbles. The studies found that PACl were effective in cold waters at low flocculation times without organic

polymer and therefore, DAF plants can consider alum with polymer or PACl as alternative coagulant strategies.

Exall and Vanloon (2000) conducted bench-scale research using different coagulants for the removal of tannic acid. They used synthetic water and coagulants to remove organic matter and found different coagulants had different effects on turbidity removal at different temperatures. The research also showed that alum was a poor cold-water coagulant even in the absence of organic matter. Low temperatures inhibit the removal of organic compounds by alum, affecting the removal of low molar mass compounds the most. Polyaluminum chloride (PACl) did not appear to be greatly sensitive to water temperature and was equally efficient at both high and low temperatures of 22°C and 5°C. However, the studies have shown that the detrimental effect of organic matter on coagulant efficiency was heightened at warm temperatures using polyaluminum hydroxysulfate (PAHS) and PACl. Exall and Vanloon (2000) also studied the effect of tannic acid concentration to understand the influence of organic matter on coagulation. Exall and Vanloon (2000) in their studies established the fact that removal of organic matter paralleled turbidity reduction, indicating that sufficient coagulation was necessary for organic matter removal, and addition of organics further increased the coagulant demand. While the impact of organic matter on alum effectiveness did not appear to be temperature dependent, the overall efficiency was severely diminished at low temperatures (Exall and Vanloon 2000; Exall and Vanloon 2001).

Malley (1995) performed bench-scale studies (using a DAF Aztec Jar tester) to determine the effects of polymer addition on bubble charge using different synthetic waters. Synthetic water studies were performed on samples containing montmorillonite clay, humic acid (HA), and a mixture of montmorillonite clay and humic acid. Cationic polymers, anionic polymers and non-ionic polymers were used during the study and an impact on bubble charge of cationic polymer was found. Cationic polymers were effective in coating bubbles resulting in charge reversal. In treating low turbidity and low color water, addition of small amount of cationic and non-ionic polyacrylamide polymer improved the percentage solids removed by flotation. On the other hand, anionic polymer was not found to be effective in treating low alkalinity and low color water. Bench-scale study also showed a promising application of cationic and non-ionic polymers to the DAF recycle line to remove particles. Malley also conducted several jar tests to determine the alum dosage and the polymer dosage required to achieve the largest removal of particle during the flotation. In studies using humic acid or humic acid/clay mixtures coagulant dosages were based on total particle removal and a minimum 50% nonpurgeable total organic carbon (NPTOC) removal. The study suggested that alum controlled NPTOC removal and small amounts of polymer dosages were needed to optimize particle removal. However, the study did not involve post DAF filtration and required pilot and full-scale confirmation.

2.3 Dissolved Air Flotation in Drinking Water System

2.3.1 Introduction

Dissolved air flotation (DAF) has been used in industry for the separation of mineral ores since the early 1900s, the separation of fibres from white water in the Scandinavian paper industry in the early 1930s, the removal of oils, greases, and fats from liquids, the treatment of industrial and domestic wastes, the cleaning of peas, wheat and coal, the thickening of sludge, and, most recently, in the production of potable water (Hopper and McCowen, 1952; Hyde 1977; Zabel 1984; Edzwald 1995).

There have been a limited number of research efforts involving the study of DAF for the treatment of drinking water. In the early 1970s, the Water Research Center (WRC) in Medmenham, England conducted extensive studies on the feasibility of treating a wide variety of waters using DAF. The studies were prompted by the successful results of DAF in South Africa and the United Kingdom (van Vuuren and van Duuren 1965; van Vuuren 1965; Hyde 1977; Longhurst and Graham 1987; van Vuuren 1995). DAF jar test results demonstrated the feasibility of treating color and low turbidity water, and further indicated that coagulation, flocculation, and adequate air supply were important for good flotation performance (Hyde 1977; Packham and Richards 1972). Color and algae-laden waters were treated effectively with aluminum salts or iron salts as coagulants, and a flocculation period of 15 minutes with a recycle ratio of 5% were required for successful flotation in the jar test (Hyde 1977). The process was found to be more effective than sedimentation in removing algae and color (Zabel 1984). The promising results from

WRC's laboratory feasibility studies led to the development of DAF pilot plants in the United Kingdom.

The Lennox Institute of Research (LIR) carried out the first studies of DAF for the treatment of drinking water supply in the United States of America in the early 1980s. The studies successfully demonstrated the treatment of highly color water with low alkalinity and turbidity using dissolved air flotation (Krofta 1981; Krofta and Wang 1982). In these studies, alum and an anionic polymer with a recycle flow of 15% pressurized at 410 kPa (60 psi) were required for removing color and turbidity. The successful results also led to the development of a continuous- flow pilot plant that combined the processes of coagulation and flocculation, dissolved air flotation, and dual media filtration into a single unit.

In Canada, the use of DAF for drinking water treatment is not widespread despite several decades of successful application in Europe. At present, there are no large DAF plants (>10 ML/d), in Canada, although several large cities faced with low turbidity and color or algae laden waters are considering the DAF technology to meet strict regulatory guidelines (Adkins 1997). DAF processes are widely used in Belgium, the Netherlands, the United Kingdom, Finland, Asia and Australia. As of 1995, there were fifteen operational DAF plants in the USA and another five were either in the planning, design or construction phase (Edzwald 1995).

2.3.2 The Dissolved Air Flotation Process

There are a number of different flotation processes applied in processing industries. Flotation processes can be described in terms of the material being removed or separated (mineral flotation, precipitate flotation, colloid flotation, and ion flotation) or by the method of bubble formation (electro flotation, dispersed air flotation, and dissolved air flotation). In DAF, the bubbles can be formed through either vacuum or pressurized methods. Vacuum DAF is limited to a pressure change of less than 1 atm (101.3 kPa) and has limited applications, mostly in wastewater sludge thickening (Edzwald 1995). When used in drinking water treatment, the DAF process incorporates pressurized methods of bubble formation. In this method, a percentage of the treated water flow is saturated with air under pressure and recycled to the head of the flotation unit. The recycle stream is injected into a flotation tank using specially designed nozzles or needle valves resulting in the formation of bubbles. Measurement of bubble sizes for DAF systems indicates that bubbles maintain a steady state size range of 10 to 100 μm (Zabel 1984; De Rijk et al. 1994). A reasonable estimate of the average bubble diameter is 40 μm (Rees 1980). The steady state size depends on the saturator pressure and injection flow rate (recycle ratio). The injection flow or recycle flow rate must provide a rapid pressure drop and be sufficient to prevent backflow and bubble growth on the pipe surface in the vicinity of the injection system (Edzwald 1995). Higher pressures produce smaller bubbles and there is a diminishing return in reducing the bubble size (De Rijk et al. 1994). To ensure small bubbles, pressure differences of 400 to 600 kPa are recommended and differences of 487 kPa are typically used. Additional bubble growth may occur as the bubbles rise in the flotation tank due to a decrease in the hydrostatic

pressure or by coalescence, and both of these have negligible effects on the small bubbles formed in DAF system (Takahashi et al. 1979).

2.3.3 Mechanism of Bubble -Particle Attachment

The possible mechanisms for forming aggregates of bubbles and particles are :(1) entrapment of preformed bubbles in large floc structures, (2) growth of bubble nuclei on particles or within the flocs, and (3) particle collision and adhesion with preformed bubbles. Entrapment of preformed bubbles is more important where larger flocs (>100 μm) already exist or are formed rapidly by high rates of flocculation involving concentrated suspensions such as those found in municipal and industrial wastewaters. While this and the second mechanism likely occur to varying degrees in all applications, the third mechanism is the most important for most applications (Edzwald 1995).

Experimental evidence has indicated that both charge neutralization and the production of hydrophobic particles are required for successful flotation. As well, the success of bubble-particle attachment is dependent on particle destabilization, which in turn is governed by coagulant dose, pH, and raw water quality (Zabel 1985; Malley and Edzwald 1991a; Malley and Edzwald 1991b; Edzwald 1995; Edzwald and Wingler 1990). Optimal coagulant conditions for DAF can be predicted by standard jar tests (Zabel 1984; Edzwald and Wingler 1990; Bunker et al. 1995; Edzwald 1995; Bodo et al. 1996). It is important to note, however, that the mechanism of bubble-particle interaction

in a dissolved air flotation contact zone is poorly understood and is usually described only by conceptual models (Shawwa and Smith 1998).

2.3.4 Practical DAF Operations

A schematic diagram of a dissolved air flotation treatment plant is shown in Figure 2-1. The DAF process includes chemical mixing, coagulation and flocculation, clarification by dissolved air flotation, filtration, and microorganism reduction. In DAF processes, treated water is drawn from the bottom of the flotation tank while the floated sludge is removed from the water surface. Float sludge can be removed by mechanical scrapers or by flooding continuously or intermittently. The DAF process can effectively remove particles just tens of micrometers in size (Edzwald et al. 1990).

A flocculation time of between 5 and 15 minutes is adequate for effective flotation. Flotation performance improves slightly with increasing flocculation mixing intensity, measured by the mean velocity gradient (G). It has been suggested that flocculation tanks be designed to produce strong and small "pin-point" size floc particles with a diameter of approximately 10 μm. However, recent studies showed that the formation of floc particles between 10 and 30 μm is favored for effective DAF performance and could be achieved at a G value of between 55 and 70 s^{-1} (Edzwald et al.1990; Edzwald et al. 1992).

The recycle flow consists of either clarified or filtered water pressurized to 480 to 585 kPa in an air saturation device. In practice, typical recycle flows between 6% and 12% are used, however, recent studies have demonstrated that recycle flows between 6% and 8% are sufficient for effective flotation (Steinbach and Haarhoff 1998).

In optimizing the saturator pressure and recycle ratio, the operation and maintenance cost for a DAF plant can be reduced. The short detention time of DAF can reduce the capital cost of treating water that would typically require detention times of up to 4 hours if conventional settling tanks were used. In general, the design parameters for DAF include detention time, overflow rate, recycle ratio and saturator pressure. Typically, overflow rates in a DAF basin are between 5 and 15 m/hr; the lowest overflow rates are used when flotation and filtration are carried out in the same reactor (Malley and Edzwald 1991a). A list of typical design and operating parameters for DAF plants is presented in Table 2-1.

The flocculation systems employed prior to DAF have been designed similar to those in sedimentation with flocculation times as long as 45 minutes (Heinänen Jokela, and Ala-Peijari 1995). Recent studies with bench and pilot-scale work have, however, shown that good flotation performance can be achieved with flocculation times of only five to ten minutes (Edzwald and Walsh 1992).

2.3.5 DAF vs. Conventional Sedimentation

The advantages of DAF over conventional sedimentation for treating low turbidity, low alkalinity, naturally colored, and algae laden waters are numerous and include the efficient removal of particles, higher surface overflow rates, shorter flocculation detention times, and higher percentage solids sludge (Edzwald 1995; Malley and Edzwald 1991b; Zabel 1984). As well, DAF produces lower turbidity and particle concentrations than conventional sedimentation in cold temperatures. Several studies have found DAF to be a viable technical alternative to the conventional gravity settler for the treatment of low turbidity waters that contain natural organic matter (Malley and Edzwald 1991b; Zabel 1984; Zabel 1985; Zabel and Melbourne 1980). Since the removal of dissolved organic compounds is similar for both DAF and conventional sedimentation, the removal of dissolved contaminants is believed to be dependent on the coagulation process and independent of the solid-liquid separation process (Edzwald 1995; Malley and Edzwald 1991b).

2.3.6 Variables Affecting DAF Performance

The effectiveness of DAF treatment is governed both by coagulation and flocculation variables as well as DAF process variables (Shawwa and Smith 2000). Regarding the former, process pH, coagulant type and dose, rapid mixing, flocculation detention time, velocity gradient, and process temperature can all impact DAF performance. It has been shown, however, that coagulation chemistry has a stronger

influence on DAF performance than physical flocculation parameters (Valade et al. 1996). Each coagulant has a specific optimum dosing range that depends on raw water characteristics. Overdosing can cause subsequent breakdown of weaker flocs. The flocculation stage encourages the growth of aggregates during slow mixing. The prime objective of this process is to transport the destabilized particles and to promote collisions and floc formation (Shawwa and Smith 2000). With regards to the DAF variables that impact process performance, the bubble size, the amount of air introduced into the system, and surface loading are all key (Zabel 1985, Edzwald 1995, Malley and Edzwald 1991b, Longhurst and Graham 1997).

The effects of temperature on coagulation and the solid-liquid separation process are poorly understood (Malley and Edzwald, 1991a.). However, there is an effect of temperature on humic water treatment. The rising velocity of floc-air bubble-agglomerate is determined by Stoke's law and therefore, it is inversely proportional to the viscosity of water and consequently, directly proportional to the temperature. High rising velocities usually result in an efficient DAF process and, therefore, low temperatures should have a negative effect on it. However, it has been found that low temperature retards the settling of flocs more than their rising in DAF. Therefore, in the winter, flotation can be a more reliable and advantageous process than sedimentation.

2.3.7 <u>Successful Applications of DAF in Water Treatment</u>

2.3.7.1 Experimental Evaluation

DAF processes are preferred over conventional sedimentation for the treatment of humic and highly colored waters. Heinänen et al. (1995) applied DAF in a number of trials to the treatment of moderately humic water with color values between 60 and 80 TCU, in Pori, Finland. The results were found to be encouraging as post-DAF color and turbidity values were 3 TCU and 0.28 NTU, respectively. Zabel and Melbourne (1980) reported that raw water of color values up to 7000 TCU were decreased to 10 to 30 TCU after DAF treatment and 6 TCU after filtration. Rees et al. (1980) conducted DAF trials at Arnfield, UK with moderately colored water with color values between 10 and 60 TCU. Color and turbidity values were reduced to 2 TCU and 0.7 NTU, respectively, after DAF treatment. In that study, however, accumulated sludge caused some operational difficulties due its tendency to break up after 30 minutes of detention time. Malley and Edzwald (1991a) found that water at Mt. Brook, Washington, with raw turbidity and color values of 0.6 to 4.3 NTU, 45 to 180 TCU, respectively, could have turbidity values reduced to less than 0.5 NTU with optimal coagulant dosing and DAF treatment. In their study, color removal was found to decrease proportionately with turbidity.

Edzwald and Walsh (1992) conducted laboratory studies at the University of Massachusetts to examine the removal of particulates, natural organic matter and algae in synthetic waters containing clay turbidity (montmorillonite clay), natural color (fulvic acid) and algae (*chlorella* and *cyclotella*) using DAF . Both bench-scale and pilot-scale

studies found DAF to be successful for the treatment of colored and algae laden water. Bench-scale studies were also conducted to compare the performance of DAF to that of conventional gravity settling for the treatment of colored water. When the same pretreatment conditions were applied, the clarification time for DAF was approximately 6 times lower than that of conventional settling. Furthermore, DAF was found to be more effective than conventional settling for the removal of turbidity and color.

2.3.7.2 Full-Scale Evaluation

With regards to full-scale DAF applications, Olson (1992) documented the operating experiences of two DAF water treatment plants used for the treatment of colored water in Pittsfield, Massachusetts (the Ashley WTP) and the Cleveland, Ohio WTP. A performance analysis revealed that the combined processes of coagulation, DAF, and filtration were adequate for the removal of particulates and natural organic matter. The raw water turbidity values were less than 2.0 NTU for both facilities, while raw water color values ranged from 27 to 70 TCU for the Ashley facility and 8 to 42 TCU for the Cleveland facility. In general, both the DAF treatment plants produced treated water with turbidity values less than 0.25 NTU and color values less than 2 TCU. Results also suggested that proper coagulation conditions are necessary for good performance of the DAF and filtration processes. Filtered water pH was found to affect the concentration of residual aluminum and DAF effluent turbidity and color (Olson 1992). Good removal of color and turbidity and the lowest residual aluminum concentrations were found when pH values in filtered water ranged between 6.2 and 6.4.

The results from Finnish treatment plants, reported by Heinänen (1988), showed that DAF was well adapted to the treatment of humic waters. The overall treatment performance of Finnish DAF facilities, as determined by the removal of turbidity and organic matter, was found to be good (Heinänen et al. 1995). This later study also suggests that proper coagulation, flotation detention time, surface overflow rate, air requirements, and recycle characteristics are important design and operating considerations for successful treatment of colored water.

Tamulonis (1992) evaluated the performance of 7 full-scale European DAF treatment plants All the facilities were found to have achieved good removal of color and turbidity in both warm and cold water temperatures. The value of pH during coagulation was found to be particularly important for successful plant operation as all facilities reported optimal operations when coagulation pH was maintained between 5.5 and 6.5.

A comprehensive survey of 18 full-scale DAF facilities in the U.K. has been conducted by Longhurst and Graham (1997). The objective of the survey was to explore principal reasons for selecting DAF and an evaluation of the performance of DAF clarifiers. Their study suggested that good flotation performance was dependent on chemical treatment, air provision, and flocculation design. The pH of coagulation was found to be the most important operating parameter for producing good removals of color.

2.4 Overview of ANN

Artificial Neural Network technique is a computational system that mimics the human brain's problem solving processes. The system trains with real data that teaches the system to find a relationship between all the input information to obtain a result. ANN systems develop models based on the different input weights assigned to input parameters. These are defined in the training process. An advantage of the system is that a deep understanding of the process is not required. However, it is necessary to know the possible factors that affect the processes.

The basics of the artificial neural networking structure, characteristics, and operation mode have been extensively described in the literature previously (Baxter et al.2002a), and will not be discussed in this thesis. However, the multi-layer perceptron network using the error back propagation-learning rule is widely used (Baxter et al. 2002a) in building models. In multi-layer perceptron architecture, neurons are arranged in layers such as an input layer, hidden layers and an output layer. This type of network can be trained to accomplish a wide variety of mappings where neurons in the hidden layers learn to respond to features found in the input patterns. Input neurons receive values of an instance of the input parameters that are fed to the network after being scaled to a numerical range which is efficient for calculations by the neural networking model. Hidden layer neurons (HLN) connect the input neurons to the output neurons and provide non-linear relationships to the network. Each neuron is connected to every neuron in adjacent layers by a connection weight. This connection weight determines the power of

the relationship between two connected neurons. The output from a neuron is multiplied by the connection weight before being introduced as input to the neuron in the next layer. Thus the input-output characteristics of a neuron and its interconnection capabilities to other neurons determine the output of the neuron. The network develops overall functionality through one or more forms of learning. Figure 2-2 shows a schematic diagram of a multi-layer neural network.

2.5 ANN Control of Water Treatment

The water industry has habitually relied on mathematical and physical models, expert systems, and knowledge-based systems in order to address the complex and non-linear treatment issues. Artificial Neural Networks (ANN) do not require an understanding of physical laws and have the ability to learn plant specific non-linear behaviour without requiring specific knowledge of underlying mechanistic relationships. Also, they do not require complicated programming or the development of complex algorithms to build a successful model (Baxter et al. 2002a). The theoretical possibilities of neural networks are unlimited and there are many examples of applications (Joo et al. 2000). The use of ANN for process modeling and control in drinking water systems is recognized as a very promising modeling tool and is considered to be a key area of research (Baxter et al. 2001a). Thus, in recent years, the development of artificial neural networks in the drinking water industry is increasing as they allow prediction of accurate

chemical dosing rates in process modeling, improved drinking water quality while reducing the operating costs, and predicting drinking water consumption more accurately than the conventional techniques. As a result, a number of published model applications in water treatment, and quality and demand forecasting, and distribution system management have been adopted by water treatment industries (Baxter et al. 2002a; Joo et al. 2000).

In water treatment, ANNs have been previously applied for prediction of alum and polymer dosage (Mirsepassi et al. 1995; Gagnon et al. 1997; Han et al. 1997), chlorine residuals in storage tanks and distribution systems (Rodriguez et al. 1997), source water salinity forecasting (DeSilets et al. 1992), chlorine dosage requirements and control (Rodriguez and Serodes 1996; Rodriguez and Serodes 1997), modeling for raw water color forecasting (Zhang and Stanley 1997), water quality parameter prediction (Maier and Dandy 1996). The most recent applications include effluent turbidity and color associated with enhanced coagulation (Stanley et al. 2000), water demand and consumption forecasting (Zhang et al. 2001; Stark et al. 2000), prediction of water main breaks (Sacluti et al. 1999), modeling of filtration performance (Tupas et al. 2000), lime dose and hardness in softening (Baxter et al. 2001a). However, the recent development and application of ANN model-based advanced process control of coagulation showed the potential significance in operational cost savings for utilities in full-scale applications in the water industry (Baxter et al. 2002b, Joo et al. 2000).

Table 2-1 Key parameters used in DAF design and operations

Parameter	Unit	Design Values Range	Typical
Chemical Pretreatment			
Coagulant Dose	mg/L	Determined from DAF jar test	
Flocculation Time	min	10 to 30	20
G-value	Sec^{-1}	10 to 150	70
Flotation tank			
Reaction Zone			
Detention Time	min	1 to 4	2
Hydraulic Loading	m/hr	20 to 100	30
Flotation Zone			
Detention Time	min	5 to 15	10
Hydraulic Loading	m/hr	5 to 15	15
Air Saturartion System			
Operating Pressure	kPa	206 to 620	485
Recycle rate	%	6 to 30	10
Air/solid Ratio	mL/g	200 to 400	380
Bubble Size	µm	10 to 120	40
Saturator efficiency	%	40 to 90	70
Sludge Removal			
Solids	%	0.2 to 6	3
Layer Thickness	mm	5 to 15	10
Sludge Scraper Speed	m/hr	15 to 50	30

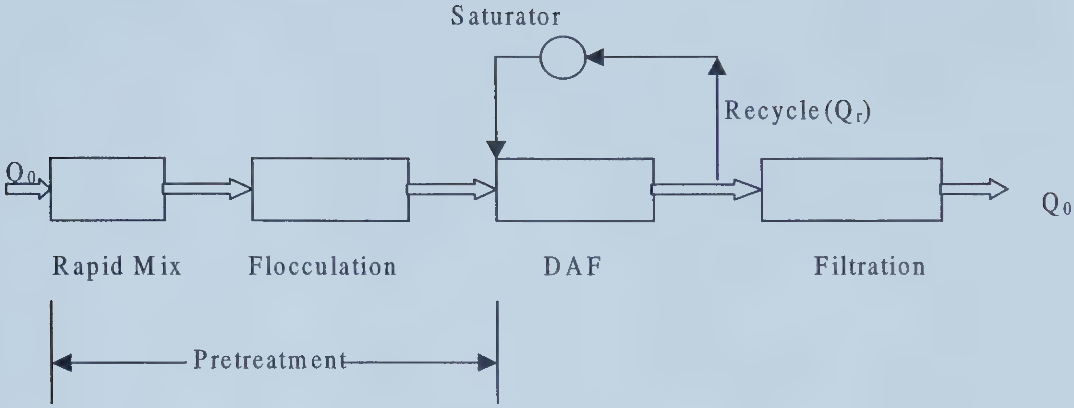

Figure 2-1 Schematic of a DAF plant

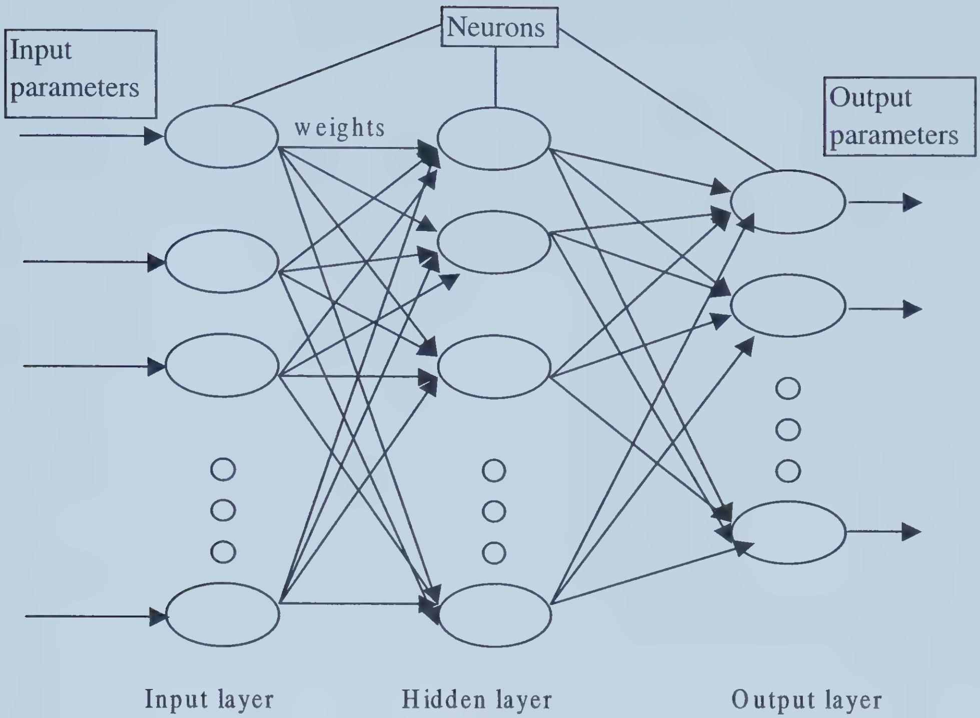

Figure 2-2 Schematic diagram of multi-layer perceptron network (MLP)

3 MATERIALS AND METHODS

3.1 Location and Raw Water Source

The bench-scale part of the research was conducted at the University of Alberta. Raw water was shipped from Port Hardy, British Columbia to the University of Alberta. The containers used for the shipment were 1.2 m^3 in volume. Two totes were used for each shipment to transfer a total amount of 2.4 m^3 of water from Port Hardy. It took almost one week to arrive in the University of Alberta premises. There were two shipments of water from September to December to conduct the bench-scale study. The raw water source was from Tsulquate River, which is a low alkalinity supply. The first supply of raw water arrived at the University in September 2002, and the shipped raw water color was 35 TCU. The second supply of raw water was in December 2002, and the raw water color was 195 TCU. The bench-scale research was conducted between August 2002 and December 2002, when the average raw water temperature at Port Hardy was 5°C. However, the bench-scale study was performed at room temperature of 21°C at the University of Alberta laboratory in the Newton Research Building (NRB). During this study period a total of 107 data sets were collected. To ensure that the raw water quality did not change over time and the container did not act as a natural sedimentation tank, the bench scale study was performed as quickly as possible. These two shipments of raw water helped in building a standard protocol for both bench-scale and pilot-scale study. The raw water characteristics of two different shipments are presented in Table 3-1, and Table 3-2.

Table 3-1 Characteristics of low-colored water

Parameter	Units	Port Hardy Water
pH		6.7
Turbidity	NTU	0.40
Color	TCU	35
Particle concentration	number/mL	915
DOC	mg/L	4.0
UV absorbance at 254 nm	cm^{-1}	0.183
Alkalinity	mg/L as $CaCO_3$	9

(*September, 2002 shipment from Port Hardy at room temperature 21°C*)

Table 3-2 Characteristics of high-colored water

Parameter	Units	Port Hardy Water
pH		6.5
Turbidity	NTU	1.30
Color	TCU	190
Particle concentration	number/mL	5482
DOC	mg/L	19.8
UV absorbance at 254 nm	cm^{-1}	0.897
Alkalinity	mg/L as $CaCO_3$	7

(December, *2002 shipment from Port Hardy at room temperature 21°C*)

The dismantled pilot plant, and the bench apparatus (Aztec jar test) along with various laboratory equipment (HACH turbidity meter, pH meter, HIAC-ROYCO particle counter, spectrophotometer, chemicals etc.) were transported to Port Hardy to collect pilot-scale and bench-scale data using fresh water at the Port Hardy Water Treatment Plant. During the study period at Port Hardy, a total of 85 data sets were collected from the pilot plant. The coagulant dosage (alum) and soda ash dosage for the pilot study were selected by mirroring dosing changes at Port Hardy Water Treatment Plant with different raw water characteristics from 22 January 2003 to 4 February 2003.

The raw water quality at Port Hardy was similar during the pilot-scale study period of 13 February 2003 to 17 February 2003. This could be due to the lack of rainfall. The raw water pH, alkalinity and conductivity did not change appreciably during the study. There was a minor change of raw water color (65.7 TCU to 66.4 TCU) and the turbidity range from (0.48 NTU to 0.49 NTU). However, these minor changes of raw water color and temperature were neglected and the experimental design was made with the assumption of using the same raw water quality. As a result, during that period (Feb 13-17, 2003) a full factorial design was followed with different alum dosages of 20, 25, 30, 35, 40, 45, 50, and 55 mg/L and alum/soda ash ratio of 0.7, 0.65, 0.6. A total 24 runs were completed.

An additional 102 data sets were collected from bench-scale testing. The data collected during the bench-scale study used a wide range of raw water quality to evaluate the bench study and build an ANN model. However, the second stage of research was

conducted from 18 January 2003 to 20 February 2003. The study also gave an opportunity to be familiar with the water treatment plant at Port Hardy and the problems associated with its operation. The average raw water temperature during the study was 5°C.

3.2 Bench-Scale DAF Experimental Protocol

The objective of this experiment was to determine the optimum coagulant dose for Port Hardy water in terms of removal of color, reduction of turbidity and particle count. Port Hardy raw water (without addition of coagulants and chemicals) was used as the control sample for the experiments. Aztec jar tester supplied by Aztec Environmental Control Limited, UK was used for these experiments. The chemical and coagulant studied are listed in Table 3-3. They included alum as reference coagulant. Soda ash was used along with alum to adjust alkalinity for better hydrolysis. Sigma-Aldrich Chemicals supplied the alum and soda ash used. The bench-scale DAF consisted of four parallel batch units. Treatment performance was monitored by measuring particle count, true color, turbidity, and UV absorbance at 254 nm (UV_{254}) as a surrogate measure for DOC (samples filtered with a 0.45 μm membrane filter) using Standard Methods (19th edition 1995).

Table 3-3 Chemical and coagulant information

General Name	Product	Specific Gravity
Aluminum Sulfate	Alum	1.345
Sodium Carbonate	Soda Ash	0.96

The components of the bench-scale DAF unit included a compressed air cylinder, a saturator (pressurization tank) and four coagulation-flocculation-flotation jars constructed with high strength acrylic with a maximum capacity of 1400 mL. The DAF unit was equipped with a series of solenoid valves and recycle timers which allowed the control of the air-saturated liquid flow from the saturator to the jars. This flow was termed recycle by convention. However, there was no actual recycle in the system. The volume of recycle as a function of timer setting at a saturator pressure of 484 kPa is shown in Figure 3-1. Each jar of the DAF unit was equipped with a retractable paddle mixer. The mixers were connected to a single speed control that could be operated at 20, 30, 40, 50, 60, 80, 100, 200, 300, or 400 rpm. Velocity gradients for the paddle mixers as a function of rpm at 20° C are shown in Figure 3-2. The DAF unit included a pressurization tank, which served as an unpacked saturator. The saturator was connected to an organic-free compressed air cylinder as the air source.

Bench-scale DAF experiments were conducted by placing 8 L of deionized water in the saturator and raising the air pressure to 484 kPa (70 psi). The saturator was then shaken with hands for about 20 to 30 seconds. The pressure would fall as the air was absorbed by the water and then rise again to the regulated pressure. The saturator was

shaken two or three times while keeping the air supply on. It was allowed to stand for a minimum of 10 minutes, shaking intermittently. Each of the flotation jars was connected to the DAF unit through the saturated water inlets at the back of each jar. To purge the feed lines, Timer 1 was set between 5 and 10 seconds and valves 1 to 4 were energized. The synchronized recycle control was selected so that Timer 1 controlled all solenoid valves. The recycle button was activated so that all the feed lines were purged with the saturated water. The residual liquid in each jar was removed. The jars were then ready to be filled with experiment water.

To determine the optimal coagulant dose, the following experimental procedures were followed:

(i) Port Hardy raw water was used for the experiment. Three jars were filled with Port Hardy water and control was used to fill the fourth jar.

(ii) Using the control DAF jar, the characteristics of the water were determined by measuring color following EPCOR standard protocols, and turbidity, particle size distribution and particle concentration following Standard Methods (19^{th} edition 1995),

(iii) Appropriate volume of coagulant dose was added to each jar to produce the desired coagulant dose and the paddle mixers were lowered,

(iv) The rapid mixing conditions were 30 seconds at a G (mean velocity gradient) of 380 s^{-1} (400 rpm) followed by flocculation mixing at G of 70 s^{-1} (100 rpm) for 20 minutes,

(v) Following flocculation mixing, the paddles were removed and the flotation solenoids were activated. A flotation recycle ratio of 10% (100 mL of saturated water released into 1000 mL of sample water) was used in all experiments. The jars were allowed to stand for 10 minutes before samples were taken,

(vi) Samples were taken from the bottom tap at the base of each jar. Prior to sampling, the sample tubing was purged with approximately 100 mL of sample to ensure the line was clear.

(vii) The optimum coagulant dose was determined based on the following criteria: treated water turbidity of 1 NTU or lower, color <5 TCU and lowest particle count in treated water (or highest particles log reduction). However, if the optimum dose could not be determined in the selected range, a new coagulant dose range was selected and the experiment was repeated.

The flocculation detention time, flotation time, saturator pressure, and recycle ratio were held constant at 20 minutes, 10 minutes, 480 kPa (70 psi) and at 10% respectively. For the conditions used in this research (70 psi, 70% saturator efficiency, and 10%

recycle ratio) bubble volume concentrations of 5600 ppm were released into the DAF jar at 20°C (Edzwald 1995, Table 1, page 9). The saturator efficiency was determined These concentrations are much higher than the particle volume concentrations for the waters tested. Therefore, the opportunity for collisions between particles and bubbles in DAF were much greater (Malley and Edzwald 1991).

3.3 Pilot Scale DAF Experimental Protocol

In this research, a continuous flow pilot-scale DAF system designed by Shawwa (1998) during his PhD studies was used. A schematic of the pilot plant used during the experiment in this study is shown in Figure 3-3. The experimental set up included a mixing column, a contact zone column, a separation zone tank, an air dosing system, a flocculation unit, and rapid mixing unit (in-line static mixer). The dimensions of the mixing zone, contact zone column and separation zone (clarifier) tank are given in Table 3-4. The dimensions of the flocculation tank are given in Table 3-5.

The raw water of Port Hardy was pumped from the reservoir using a variable flow peristaltic pump, first to the in-line static mixer and then to the flocculator. The desired flow rate was determined and maintained by using a calibrated flow meter (maximum capacity of 15 L/min). The coagulant and soda ash were pumped from small reservoirs into the in-line static mixer, through a one-way valve, by using small peristaltic pumps. The calibration curves for pump I (controlled alum dose) and pump II (controlled soda-ash dose) are presented in Figure 3-4 and Figure 3-5. The in-line static mixer provided

rapid mixing of coagulant for particle charge neutralization. The objective of the rapid mixing was to disperse the coagulant in raw water as rapidly as possible (less than 1 second) and at high intensities of mixing (G values of 3000 to 4000 s^{-1}). The coagulated water entered the flocculator tank (0.04 m^3). Slow mixing was accomplished by using a variable speed motor, which provided a mixing intensity (G) of 70 s^{-1} using a six-flat-blade turbine connected through a vertical shaft to a variable speed motor. The flocculator was elevated to create enough head for the water to flow by gravity to the DAF mixing column at the preferred flow. The flow rate entering the column was controlled by a ball valve located at the flocculator effluent line. The flocculator was designed with an overflow weir so that the water head in the tank was always constant. The overflow water was collected in a launder and discharged through the waste line.

The air dosing system was used to produce supersaturated water, which was injected into the contact zone to produce fine bubbles. The bubble volume concentration can be controlled by the recycle ratio (R_R), which was defined as Q_{sat} divided by Q_{water}. However, Q_{sat} was the volumetric flow rate of saturated water and Q_{water} was the volumetric flow rate of DAF influent water. Saturated water was injected into the DAF mixing column by means of a specially designed nozzle which was located below the flocculated water feeding point. The contact zone hydraulic loading rate was based on the total water flow rate (Q_{total}), which was equal to the flocculated water flow rate (Q_{water}) plus the saturated water flow rate (Q_{sat}) divided by the maximum cross sectional area of the contact zone. The saturated water flow rate was regulated by means of a needle valve. The flow rate was determined by using a calibrated flow meter which could read from 0

mL/min to 1250 mL/min. The rising bubble-floc agglomerates were collected on top of the separation zone tank. The clarified water exited through the bottom of the clarification tank through a plastic tube connected to a level adjustment pipe. The pipe was used to control the water level inside the clarification tank so that water level could be adjusted to remove the foam layer through the launder and discharged through the waste line whenever required. Another line through the bottom of the clarification tank went through an online particle counter, which could measure the particle count of the DAF effluent.

The experiments were conducted with the following procedure:

(i) The raw water was pumped from the reservoir to the flocculator tank through the in-line static mixer. The Q_{floc} was regulated by means of a ball valve located in the flocculation of the effluent line. At the beginning of each experiment the ball valve was adjusted by measuring the flow rate exiting the DAF effluent line using the bucket and stop watch method and adjusting the ball valve accordingly. The flocculator and the DAF columns were drained completely once the desired Q_{floc} was set.

(ii) The coagulant pump and the chemical feed pump (for soda ash) were immediately started and the flow rate of the feed pump was adjusted using the calibration curve from Figure 3-4 and Figure 3-5 so that the concentration of the coagulants and soda ash solution entering the in-line

static mixer was equal to the optimum dose determined during the bench scale DAF study or the dose as desired during the run.

(iii) The calibration curve shown in Figure 3-4 was used to set the pump control settings for alum feed. The calibration curve shown in Figure 3-5 was used to set the pump control settings for soda ash feeding.

(iv) The flocculation mixer was started and the mixer speed was adjusted so that the velocity gradient G ($70s^{-1}$) was achieved. The calibration curve shown in Figure 3-6 was used to determine the required motor speed to achieve required G value of $70\ s^{-1}$.

(v) The saturated water flow rate was started by turning on the on –off valve and the required flow rate was adjusted by means of the needle valve to match the required recycle ratio. The saturator tanks were filled with deionized water and pressurized at 484 kPa a head of the start of the experiment to allow enough time for saturation. The tanks were shaken intermittently for about 10 minutes.

(vi) After about four times of the total detention time of the pilot scale DAF (the system achieve steady-state condition), water sample was collected for turbidity, color, particle count and pH analysis.

Table 3-4 Summary of contact zone, mixing column and separation zone tank dimensions

Design Parameter	Units	Dimensions
<u>Contact zone column</u>		
Height	mm	1200
Max Diameter	mm	100
Minimum Diameter	mm	40
Height of cone	mm	300
<u>Mixing column</u>		
Height	mm	500
Diameter	mm	40
<u>Separation Zone</u>		
Height	mm	700
Diameter	mm	400
Volume	m^3	0.0879

Table 3-5 Summary of flocculation tank dimensions

Design Parameter	Units	Dimensions
Tank side depth	mm	450
Tank width	mm	300
Tank length	mm	300
Baffles	number	4
Baffle's width	mm	35
Impeller diameter	mm	120
Impeller height above tank's bottom	mm	120
Flat blades	number	6
Blade width	mm	25
Blade length	mm	30

3.4 Analytical Methods

Color, turbidity, and particle counts were the main parameters measured to assess DAF performance. Analyses were conducted on-site in the University of Alberta laboratories or in the Port Hardy Water Treatment Plant laboratory. In general, the methods followed Standard Methods (19^{th} edition 1995) or comparable EPCOR standard protocols. Raw water quality parameters such as the raw water temperature, the raw water color, the raw water turbidity, the raw water alkalinity, and the raw water conductivity were measured at the University of Alberta and Port Hardy Water Treatment Plant laboratory using Standard Methods (19^{th} edition 1995).

During the bench scale study, total number of particles per mL was monitored using a HIAC/ROYCO particle counter (model 8000, Pacific Scientific, Silver Spring, Maryland). The particle counter sensor had a size range of 1 to150 μm with a maximum particle concentration of 16,000 particles greater than 1.0 μm/mL. For the pilot plant study, the water sample was collected from the bottom of the clarifier. One on-line particle counter (MET ONE) provided by EPCOR water services was used to measure the number of particles and determined the particle size distribution (PSDs) during the pilot study. The on-line particle counter was connected at the bottom of the clarifier just beside the DAF effluent water line. There was a continuous flow of treated water (100 mL/min) through the online particle counter from the bottom of the clarifier.

Turbidity and pH was measured using an analog turbid meter (Model 2100A, HACH, Loveland, CO) and an analog pH meter (Ion-analyzer /Model 399A, Orion Research, Cambridge, Massachusetts), respectively. The analysis of color during the bench scale and pilot study was conducted using the EPCOR protocol. The detailed method is in Appendix A. The standard curve for measuring color (Pt-Co unit) is shown in Figure **3-7**.

3.5 Data Collection and Handling

Three types of data were collected in order to develop bench-scale, pilot-scale and full-scale model during the research study. These include raw water quality data, process data, and performance data. The raw water quality data included temperature, pH, alkalinity, color, particle count, turbidity, and conductivity. Process data included plant flow data, coagulant dose and chemical dose. The performance data may include effluent parameter data like effluent turbidity, particle count, color etc.

3.5.1 Full-Scale Data Collection

Full-scale artificial neural network models were developed and trained using historical data. The quality of the developed model was highly dependent on the source data used (Baxter et al., 2001a). The artificial neural network model was developed using

one-year daily average data from November 2001 to October 2002, obtained from the EPCOR Water Services, Port Hardy Water Treatment Plant, BC, Canada.

Raw water pH, conductivity, and temperature were measured daily and alkalinity was measured weekly by the plant operator. Raw water turbidity, color, particle count were measured on line and stored by a SCADA system. Three parameters turbidity, color and particle count of the DAF effluent were selected as performance parameters. These performance parameters were also measured online and stored by a SCADA system.

Data records of raw water entering the DAF treatment plant were downloaded from the SCADA system at Port Hardy water treatment plant from November 2001 to October 2002. Data patterns were at 1-hour intervals. There were a lot of noisy data patterns with questionable entries and several plant shutdowns. The daily average data patterns were further developed from one-hour interval data. Models were developed using daily average data. Scatter plots of each variable was used to detect faulty data. Data patterns containing questionable data was removed and a record was maintained for future reference.

3.5.2 Pilot-Scale Data Collection and Handling

Artificial neural network models were developed and trained in pilot-scale operation. The pilot plant was operated at Port Hardy Water Treatment Plant by emulating the full-scale DAF, and 85 data sets were collected during the study.

Raw water pH, conductivity, temperature, alkalinity, turbidity, and particle count were measured and recorded prior to each run. Data included raw water quality parameters (such as temperature, pH, conductivity, turbidity, color, and alkalinity); process parameters (such as alum dose, soda ash dose, and plant flow). Alum dose, and soda ash dose were mirrored from the full-scale plant. The pilot-plant was operated at different flow rates.

Turbidity, color and particle count were selected as performance parameters. The particle counts were measured both online and bench top, and the turbidity and color values were measured at the lab.

3.5.3 Bench-Scale Data Collection

The first stage of bench-scale testing was carried out at the University of Alberta using shipped water from Port Hardy at the first stage of the research. During the second stage of the research, the bench-scale equipment was operated at Port Hardy Water Treatment Plant using fresh raw water. A total of 210 data sets were collected during the study period.

Conductivity, pH, temperature, alkalinity, turbidity, particle count, andUV_{254} absorbance of the raw water were collected. Raw water pH, turbidity, particle count, and color were measured at the laboratory prior to each run. UV_{254} absorbance and DOC of

the raw water were measured occasionally. The optimum coagulant and chemical dose were determined by increasing doses.

Turbidity, color, and particle count of the DAF bench-scale operation were selected as performance parameters and were measured after each run. UV absorbance was also measured occasionally after the run.

3.6 ANN Model Development Protocol

Three key stages were followed to develop a successful ANN model (Baxter et al. 2002a). These were data collection and analysis, application of the model development protocol, and model performance evaluation. The model development protocol includes identifying input and output parameters, organizing data patterns, setting architecture characteristics, model stability evaluation and fine tuning of the model.

To ensure the development of a good model, a thorough analysis of data sets was performed. Data were fully characterized and a descriptive statistical analysis was performed. The statistical analysis involved determination of measures of central tendency, measures of variation, a percentile analysis, and the identification of outliers, erroneous entries, and non-entries of each data variable. Scatter plots of each variable were used to identify outlier values.

Successful model development involved the optimization of modeling parameters (Stanley et al., 2000). The numbers of input parameters were selected based on available literature review (data for each of the variables known or suspected to affect the process being modeled), data availability and good engineering knowledge. Drinking water treatment processes were considered to be multiple-input multiple-output (MIMO) and hence the process models had multiple output variables. The ANN technique yields better results when a single output is used (Baxter et al 2001a) and therefore, models were developed for each single output to reduce overall prediction errors.

Data patterns were first sorted according to the value of output variable and then assigned to data sets classified in three categories: training, testing and production in a ratio of 3:1:1, respectively. After training a neural network on a data set, the network has to be tested against a validation or testing data set that has never been used by the network during the training period. The testing and production data set work as validation and determine the performance of the network. However, this 3:1:1 ratio for training, testing and production, respectively, has proven to be effective for many process models (Baxter et al. 2001b). ANOVA (analysis of variance) was performed on each data set (training, testing and production) to make sure that each data set was fully representative of the study domain.

The success in applying neural networks to many engineering problems has been mainly due to the achievements of the multi-layer feed-forward neural network architecture with back propagation training algorithm (Baxter et al. 2001a). The

successful process model was usually developed using a hidden layer, a linear scaling function in the input layer, logistic activation functions in the hidden and output layers, random initial weight values, and a backpropagation learning rule (Stanley et al., 2000). The ANN used in this research was based on a standard three layer (one input layer, one hidden layer and one output layer), feed-forward and backpropagation (the most common learning rule employed in process modeling) for supervised learning. The neurons in the input layer are equal to the number of input variables. The number of hidden layers neurons is determined experimentally to identify the best models.

The best model was selected based on the smallest prediction error. The prediction error was assessed with the lowest mean absolute error (MAE) and with high coefficient of multiple regression (R^2) applied to the production set. The R^2 value ranges from 0 to 1. The perfect fit would result in close to 1; very good fit near 1 and very poor fit closer to 0 (Baxter et al. 2002a). The coefficient of multiple regression is mathematically described in Equation 3-1.

$$R^2 = 1 - \frac{\sum_{i=1}^{i=n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{i=n}(y_i - \bar{y})^2} \qquad \textbf{Equation 3-1}$$

Where, y_i is actual output value, $\hat{y}_i$ is output value predicted by the ANN model, $\bar{y}$ is mean of y values, and n is total number of data.

3.7 Software used

The ANN model was developed using NeuroShell 2, Release 3.0 from Ward Systems Group, Inc., Frederick, Maryland, USA running on Pentium III PCs with Microsoft Windows 98 (second edition) operating system. The software was completely compatible with Microsoft Excel spreadsheets, and windows-based interface.

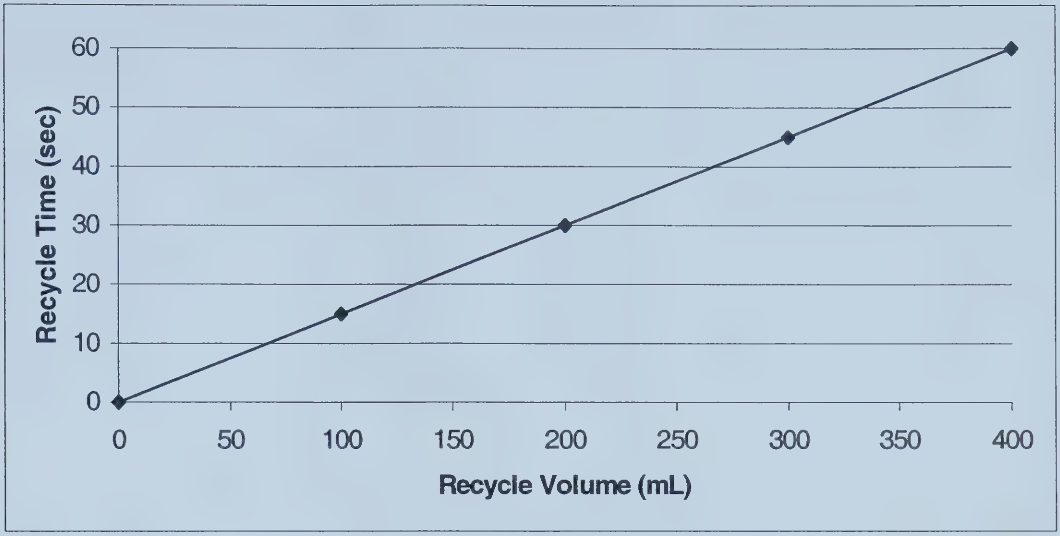

Figure 3-1 Bench-scale DAF recycles volumes vs. recycle time at saturator pressure of 484 kPa (Source: Aztec Jar Test Manual 1992).

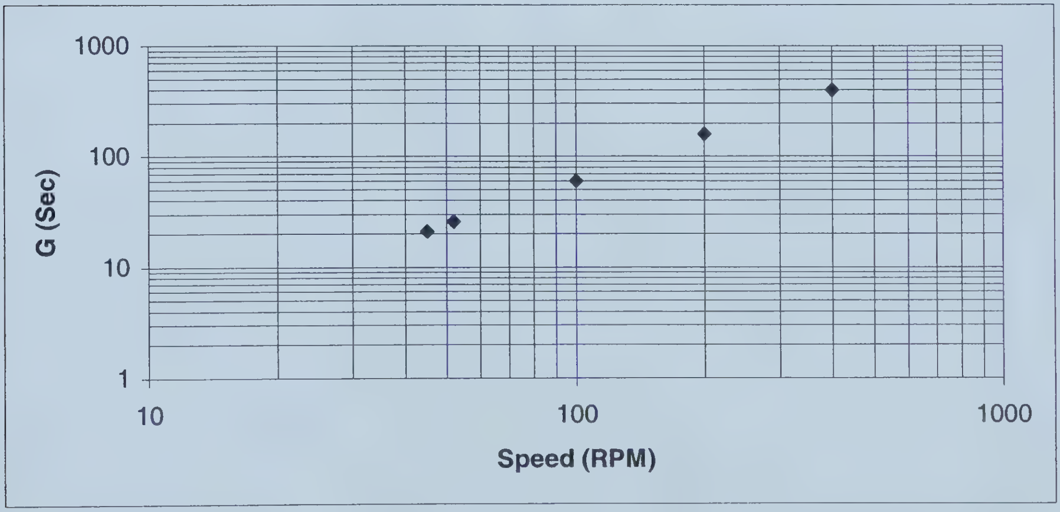

Figure 3-2 Bench-scale DAF units Velocity gradient "G" (sec^{-1}) at various speeds (RPM) at 20°C (Source: Aztec Jar Test Manual 1992).

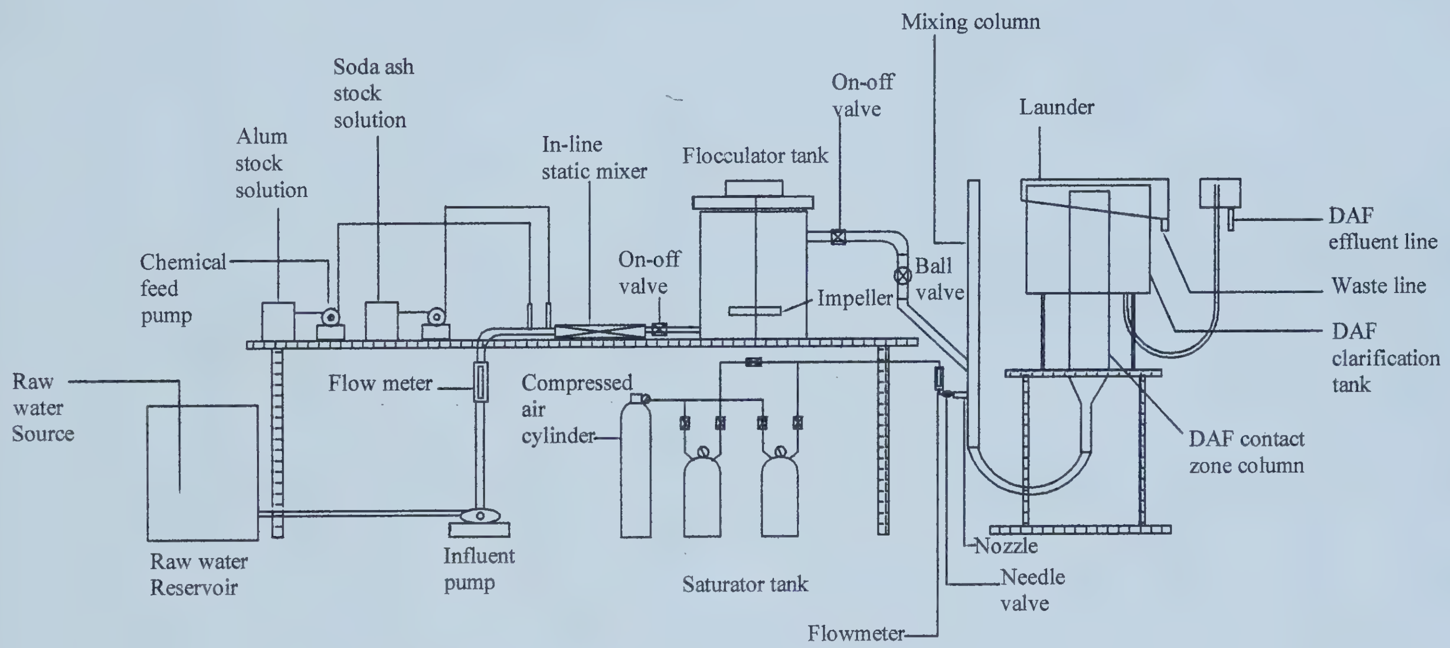

Figure 3.3 Schematic diagram of DAF pilot plant.

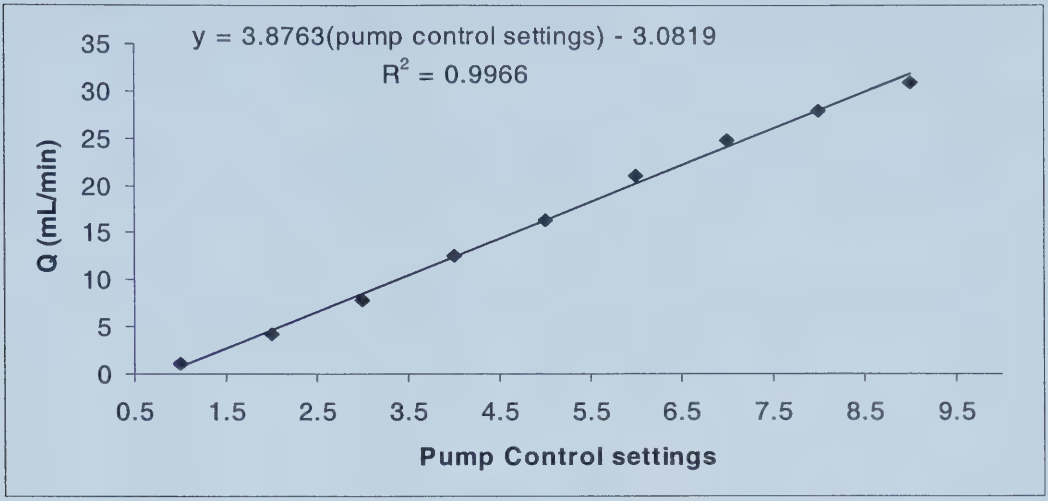

Figure 3-4 Coagulant pump (I) calibration curve.

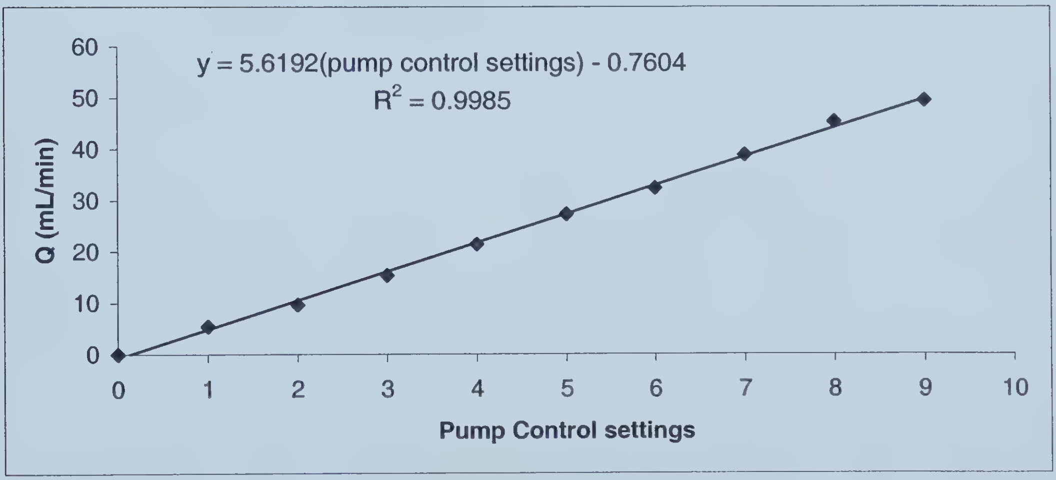

Figure 3-5 Coagulant pump (II) calibration curve.

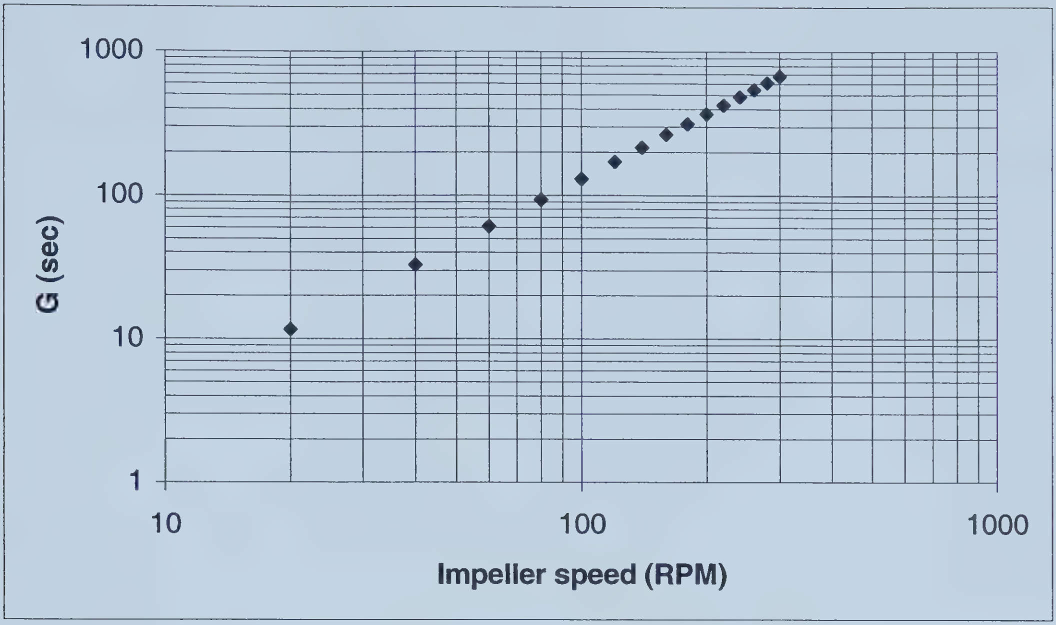

Figure 3-6 Pilot-scale flocculator mixer velocity gradient "G" (sec^{-1}) at various speeds (RPM) at 20°C.

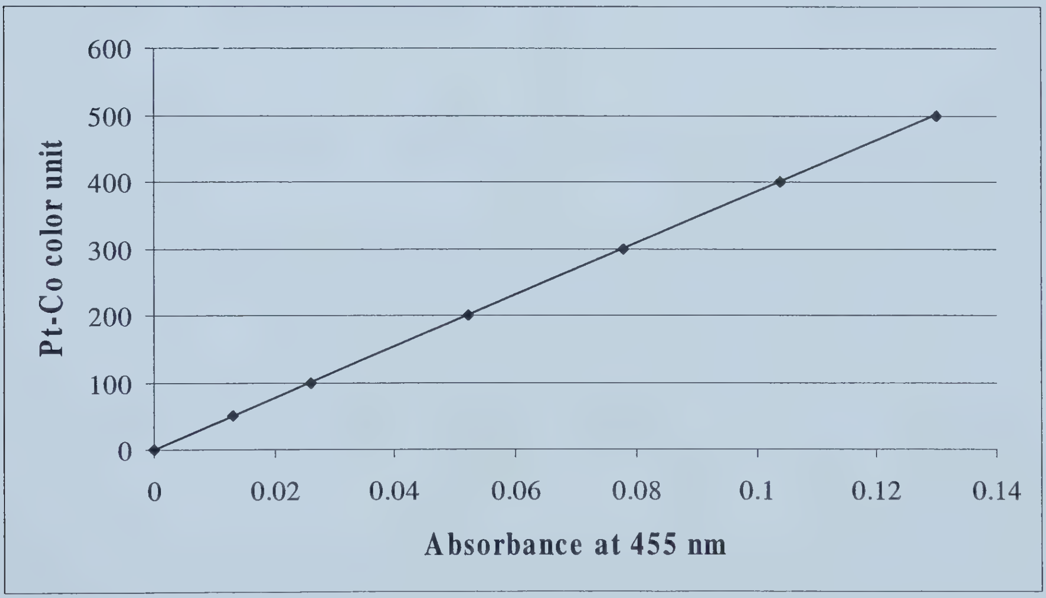

Figure 3-7 Standard curve for measuring color (Pt-Co color unit).

4 RESULTS

4.1 Full-scale

4.1.1 Source Data Analysis

The raw water quality parameters monitored at Port Hardy Water Treatment Plant, are raw water color, turbidity, particle count, pH, temperature, conductivity, and alkalinity. The raw water daily average color ranges from 30 TCU to 179 TCU, and turbidity ranges from 0.24 NTU to 4.48 NTU throughout the year. Other parameters such as temperature, alkalinity, conductivity, and pH vary from 1°C to 18°C, 1 mg/L to 46 mg/L as $CaCO_3$, 11 µS/cm to 88 µS/cm and 6.2 to 6.9, respectively. There were few faulty peaks of conductivity and alkalinity in the graphical presentation over time. Alkalinity and conductivity are entered manually in the system and there is a possibility of entering wrong data. This was further verified by talking to the plant operator at Port Hardy Water Treatment Plant and the faulty data were removed from the data set. Temperature changes over the year indicate a lot of seasonal variation and are presented in Figure 4-1. Variation of raw water flow, pH, alkalinity, and conductivity are presented in Figure 4-2, Figure 4-3, Figure 4-4 and Figure 4-5, respectively. The variation of coagulant dose and chemical dose is presented in Figure 4-6. The seasonal change of raw water color, and turbidity are presented in Figure 4-7 and Figure 4-8, respectively. The results of descriptive statistical analysis for the raw water quality parameters are presented in Table 4-1.

With respect to the operating conditions at Port Hardy Water Treatment Plant, the operator controls raw water flow, alum dose and soda ash dose. The mean raw water flow through the treatment plant was 210 m^3/hr. The daily average alum dose varied from 21 mg/L to 123 mg/L; while the average soda ash dosing rate varies from 17 mg/L to 88 mg/L. The higher dosing rates were observed only a few times during the study period. There is a strong correlation between alum dose and soda ash dose of 0.85, between alum dose and raw water color of 0.88, and between soda ash dose and raw water color of 0.80. These strong correlations suggest the dependence of coagulant and chemical dose on the variation of raw water color over time. The correlation matrix between each variable of the historical data is presented in Table 4-2.

The DAF performance as well as overall performance of process control of the Port Hardy Water Treatment Plant was measured by effluent color, effluent turbidity and effluent particle count. The average effluent turbidity and effluent color varied from 0.17 NTU to 0.98 NTU and 0.5 TCU to 58.4 TCU. The higher effluent color indicated the possibility of a plant upset and shutdown. The acceptable DAF effluent color is below 10 TCU when the raw water color is low (0 to 60 TCU) to medium (60 to 110 TCU), and below 15 TCU when the raw water color is very high (110 TCU and above).

During the months of September and October 2002, the analyzer was reading constant effluent color. This could be due to a possible analyzer breakage. These data patterns were removed while building the model for predicting DAF effluent color. However, the effluent turbidity was accurate during this period and was not removed

from the data set. The effluent turbidity as well as the effluent color did not show any seasonal variation.

The average effluent color during the month of September 2002 and October 2002 was constant at 14.8 TCU. This could be due to a possible analyzer breakage in the plant or if the DAF effluent color was not measured online for that period of time. The system was reading the last data (14.8 TCU) during this period and the repetition happened for almost 55 consecutive days. However, these faulty data cannot be replaced by the daily lab measurement of DAF effluent color at Port Hardy, as measurements were taken once every day and are not representative of the daily average data (DAF effluent color from the period of 6th September 2002 to 31st October 2002). As a result the color data were discarded from data sets during the period of 6th September 2002 to 31st October 2002. The results of descriptive statistical analysis are presented in Table 4-1.

Table 4-1 Descriptive statistics of Port Hardy Water Treatment Plant (daily average data November 2001 to October 2002)

	Average	Stdev	Var	Min	Max	Percentile P0.05	Percentile P0.50	Percentile P0.95
Turbidity (NTU)	0.75	0.56	0.31	0.24	3.99	0.27	0.55	1.83
pH	6.6	0.1	0.01	6.2	6.9	6.4	6.6	6.8
Flow rate (cum/hr)	210	26	667	155	298	176	210	263
Color (TCU)	67.3	22.4	502.1	30.2	157.3	35.9	64.3	108.0
Temp. (^{o}C)	8	5	23	1	18	2	8	16
Conductivity (μS/cm)	18	7	46	11	88	13	17	25
Alkalinity (mg/L)	4	4	16	1	46	1	3	6
Alum (mg/L)	49	18	317	21	123	23	48	84
Soda Ash (mg/L)	35	10	109	17	88	19	34	51
DAF Eff. Turbidity (NTU)	0.30	0.08	0.01	0.17	0.98	0.22	0.29	0.42
DAF Eff. Color (TCU)	6.9	5.6	31.3	0.5	58.4	1.5	5.2	14.8

Table 4-2 Correlation matrix between the variables (daily average data November 2001 to October 2002)

	Turbidity	pH	Flow rate	Color	Temp.	Cond.	Alk.	Alum	Soda Ash	Eff. Turbidity	Eff. Color
Turbidity	1.00										
pH	-0.28	1.00									
Flow rate	-0.14	0.07	1.00								
Color	0.58	-0.42	-0.24	1.00							
Temp.	-0.21	0.29	0.41	-0.32	1.00						
Conductivity	-0.09	0.12	0.25	0.02	0.46	1.00					
Alkalinity	0.05	0.16	0.02	-0.10	0.29	0.10	1.00				
Alum	0.52	-0.43	-0.25	0.88	-0.39	0.02	-0.13	1.00			
Soda Ash	0.51	-0.43	-0.30	0.80	-0.39	-0.07	-0.13	0.85	1.00		
Eff. Turbidity	0.31	-0.41	-0.06	0.51	-0.43	0.14	-0.15	0.55	0.45	1.00	
Eff. Color	-0.19	0.19	0.00	-0.04	0.45	0.32	0.11	-0.07	-0.16	-0.14	1.00

4.1.2 Selection of input and output parameters

Raw water pH, turbidity, color, conductivity, alkalinity and temperature, were classified as monitoring parameters. For the coagulants used in the coagulation process, pH is an important factor for the coagulants used, which determines the concentration of hydroxide precipitation. Alkalinity of the raw water acts as a buffer to the pH of the system. Turbidity is a surrogate measure of suspended particulates and raw water color is a surrogate measure of organic content of the water. Raw water color serves as an index to determine the alum and soda ash doses ratio in the Port Hardy Water Treatment Plant. Low temperature hinders the process by slowing down the reaction rates of the coagulants and increases the viscosity. Temperature was included as an input parameter to investigate the temperature effect on the modeling.

Similarly alum and soda ash dose and the parameter of the hydraulic control such as overflow rate were used as operational control parameters were included to build ANN

models. Similarly, over flow rate can have an important impact on the performance of the plant. High over flow rate reduces the effectiveness of floc particle agglomeration. Low flow rate is not economically feasible for the water treatment plant. Alum dose is the key operational parameter for the coagulation process. As each mg/L of alum used approximately 0.5 mg/L of alkalinity as $CaCO_3$, soda ash was used for maintaining pH (between 6.3 to 6.8) of the clarifier and DAF effluent as well as for better hydrolysis. However, as it was, alkalinity in the form of Na_2CO_3 had been spiked into the raw water, which has very low alkalinity, to provide some buffering action once the alum was dosed.

However, while building the model, all the input parameters that might influence the performance of the model output were considered and those found to be less important were removed in subsequent trials to ensure that the best model were obtained. DAF effluent turbidity, color and overall particle count are the ideal candidates as output parameters to measure process performance. Turbidity is a surrogate measure of particle count and there is a high possibility of errors associated with the particle count reading from the DAF effluent. Therefore, two parameters such as color and turbidity were chosen as performance parameters for building the models. Figure 4-9 shows the variation of daily average DAF effluent turbidity over one year period. The study suggests that the daily average DAF effluent turbidity was consistently below 1 NTU under various raw water conditions and its 95th percentile value was 0.42 NTU, which is much lower than 0.50 NTU. The DAF effluent turbidity was very much consistent with an average of 0.30 NTU and standard deviation of 0.08 NTU. On the other hand, the daily average DAF effluent color fluctuate with a mean of 7.5 TCU and a standard

deviation of 9.4 TCU. Figure 4-10 shows the variation of average DAF effluent color over the one year period. The input parameters used to build the best color model and turbidity model are presented at Table 4.3.

Table 4-3 Full-scale DAF model input parameters

DAF effluent color model	DAF effluent turbidity model
Temperature (°C)	Temperature (°C)
pH	pH
Color (TCU)	Alkalinity (mg/L as $CaCO_3$)
Flow rate (m^3/hr)	Conductivity (μS/cm)
Alum dose (mg/L)	Turbidity (NTU)
	Flow rate (m^3/hr)
	Alum dose (mg/L)

4.1.3 Selection and Organization of Data Patterns

Two different ANN models were developed to predict DAF effluent turbidity and DAF effluent color to evaluate the performance of the DAF treatment plant at Port Hardy Water Treatment Plant. Two different modeling data sets were used for building the ANN color model and the ANN turbidity model. The color model data set consisted of 254 data

patterns and the turbidity model data set consisted of 332 data patterns. Erroneous entries and questionable data patterns were removed from both data sets.

It is important to know that the DAF effluent color measurements less than 10 TCU were not reliable due to an instrumental deficiency. Therefore, there were a lot of problems developing a color model using the traditional method of sorting the data patterns according to the DAF effluent color. As such, an advanced sorting mechanism using a Kohonen Neural Network (KNN) was used (Kohonen 1982). The data records were clustered using the Kohonen self-organizing feature maps (SOFMs) into 36 categories. The data sets were first categorized into six categories is based on water quality parameters. Each category was split into a further into six categories based on operational parameters such as alum doses and flow rate, which resulted in a total of 36 categories (6 by 6 grid). All variables involved in SOFM training were left at their software defaults. The size of the grid was determined experimentally. Since each category represents separate cluster in the data sets, they were numbered from 0 to 36. Then the data patterns were separated into the training, testing and production data sets in each category to ensure that each of these had records from each of the 36 categories in the model data sets. The same 3:1:1 ratio was used to separate the patterns into training, testing and validation data sets. Therefore, the instrumental deficiency was taken care of using Kohonen self-organizing maps as a means of advanced sorting mechanism to build the color modelling data sets. The modelling data sets consisted of 152 training data patterns, 51 testing data patterns, and 51 production data patterns.

An ANOVA was performed on entire training, testing and production data patterns to ensure that all three data sets are statistically similar with regards to the mean values for each variable.

The turbidity model was built using the traditional method discussed in the methodology section. The data patterns were sorted according to DAF effluent turbidity and separated into the training, testing and production data sets using 3:1:1 ratio, respectively. An ANOVA was further performed on the entire training, testing and production data patterns. This analysis also ensured that all three data sets were statistically similar with regards to the mean values for each variable. There were 199 training patterns, 66 testing patterns and 66 production patterns used in developing an ANN model to predict DAF effluent turbidity. A descriptive statistical analysis of selected data patterns for developing the ANN models for predicting effluent color and turbidity are given in Table 4-4 and Table 4-5, respectively.

Table 4-4 Statistical analyses of model data patterns for color model

							Percentile	
	Average	Stdev	Var	Min	Max	P 0.05	P 0.50	P 0.95
pH	6.6	0.1	0.0	6.3	6.9	6.4	6.6	6.8
Color (TCU)	66.2	19.5	380.5	30.2	135.4	36.3	64.7	101.8
Temp. (celcius)	7	5	25	1	18	2	6	16
Flow rate (cum/hr	210	25	649	155	298	175	212	260
Alum (mg/L)	49	16	256	21	91	23	49	80
Eff. Color (TCU)	4.5	2.4	5.8	0.5	11.0	1.2	4.0	8.8

Table 4-5 Statistical analyses of model data patterns for turbidity model

	Average	Stdev	Var	Min	Max	Percentile P 0.05	P 0.50	P 0.95
Turbidity (NTU)	0.73	0.54	0.29	0.24	3.99	0.28	0.55	1.77
pH	6.6	0.1	0.0	6.3	6.9	6.4	6.6	6.8
Flow rate (cum/hr)	210	25	634	155	298	176	210	255
Temp.(celcius)	8	5	23	1	18	2	7	16
Conductivity (μS/cm)	17	4	13	11	34	12	16	23
Alkalinity (mg/L)	3	1	2	1	11	1	3	6
Alum (mg/L)	49	16	270	21	99	23	48	80
Eff. Turbidity (NTU)	0.29	0.06	0.00	0.17	0.47	0.22	0.29	0.39

4.1.4 Architecture of the Neural Model

Three-layer multi-layer perceptron (MLP) architecture was used to develop the ANN models. The models were developed using a linear scaling function in the input layer, a logistic activation function in the hidden and output layers, and the back-propagation learning rule. The number of hidden layer neurons was evaluated by changing number over the range of 1 to 40. The best result for the color model was obtained using 14 neurons in the hidden layer. When applied to the production data set the color model demonstrated good predictive capacity with a mean absolute error of 1.2 TCU. The best result for the turbidity model was obtained using 16 neurons in hidden layer. The turbidity model demonstrated predictive capacity with a mean absolute error of 0.03 NTU. The evaluation of the best models obtained from this data set is presented in Table 4-6 for the color model and in Table 4-7 for the turbidity model.

Table 4-6 Modeling and cross validation results on color model

Data set	R^2	Mean absolute error (TCU)
Training	0.60	1.2
Testing	0.58	1.3
Production	0.66	1.2
Production (cross-validation)	0.61	1.3

Table 4-7 Modeling and cross validation results on turbidity model

Data set	R^2	Mean absolute error (NTU)
Training	0.67	0.03
Testing	0.63	0.03
Production	0.64	0.03
Production (cross-validation)	0.63	0.03

4.1.5 Model Stability Evaluation

The cross validation technique (Baxter et al 2002a) was employed on both the data sets and further ensured that the model performance was not a function of the extracted data sets. Cross validation results on production data sets are presented in Table 4.6 and Table 4.7 for the color model and the turbidity model, respectively. The difference of mean absolute error between the original model results and the cross-validation model results is very small.

The results for all the data patterns for the color model are depicted graphically in Figure 4-11. The results for the validation data patterns are depicted graphically in Figure 4-12. The model residuals (TCU) vs. predicted DAF effluent color (TCU) for the production data patterns are presented in Figure 4-13. Absolute error (TCU) distribution of the color model for production data patterns is presented in Figure 4-14. The results for all the data patterns for the turbidity removal model from full-scale DAF at Port Hardy Water Treatment Plant are depicted graphically in Figure 4-15. The results for the validation data patterns are depicted graphically in Figure 4-16. The model residuals (NTU) vs. predicted DAF effluent turbidity (NTU) for the production data set are presented in Figure 4-17. The distribution of absolute error of the turbidity model for production data patterns are presented in Figure 4-18.

4.2 Pilot-Scale DAF

4.2.1 Source Data Analysis

The DAF pilot study was performed at Port Hardy Water Treatment Plant and a total number of 85 data patterns was collected during the study. Each data record represents water quality and operational data. A detailed analysis of the data patterns was made. The data were fully characterized and detailed statistical analyses were also performed using Microsoft Excel 2000. Scatter plots of each variable were used to detect outlier values.

During the study, the raw water quality parameters were selected as color, turbidity, particle count, pH, temperature, conductivity, and alkalinity. The variation of the raw water color, the raw water turbidity and the raw water particle during the pilot-scale study are presented in Table 4-8.However, it was observed that during a sunny day, without any rainfall, the Tsulquate River water color does not change and remains almost steady. As stated earlier turbidity is a surrogate measure of overall particle count. The lowest pH was observed during the winter storm event when the raw water color went as high as 130 TCU. This was possibly due to the presence of tannic acid at higher concentration. Temperature changes over the study are presented in Figure 4-19. Variation of raw water pH, alkalinity, and conductivity are presented in Figure 4-20, Figure 4-21, and Figure 4-22, respectively and variations of raw water color and turbidity are presented in Figure 4-23, and Figure 4-24, respectively.

Raw water flow, alum dose and soda ash dose are the part of process parameters. The plant flow rate varied from 1.8 L/min to 3.6 L/min with an average flow of 2.0 L/min and standard deviation of 0.3 L/min. The alum dose varied from 20 mg/L to 90 mg/L, while the soda ash dosing rate varied from 12 mg/L to 61 mg/L. The pilot plant was operated with higher flow rate of 3.6 L/min only at run 5. During the higher flow rate, it was found that the pilot plant did not perform better and the short detention time at the clarifier and contact zone column did not remove overall particle count efficiently. This could be due to low detention time at the clarifier tank and flocculation tank of the pilot DAF unit. Thus the data pattern with 3.6 L/min flow rate was considered an outlier and was removed from the data set. The DAF pilot plant operated well at a lower flow rate of

1.8 L/min, which gave a hydraulic loading rate similar to the full-scale DAF treatment plant. However, two different flow rates of 1.8 L/min and 2.4 L/min were chosen to operate the DAF pilot plant for the study. A strong correlation of 0.99 was found between alum dose and soda ash dose, and between soda ash and raw water color (0.84). These strong correlations suggest the dependent nature of coagulant and chemical dose in raw water color. The plant flow rate at different runs and the coagulant doses and chemical doses are presented in Figure 4-25 and Figure 4-26, respectively.

The performance of the DAF pilot plant was measured by effluent color, turbidity and particle count. The variation of the DAF effluent turbidity, the effluent color and the particle counts are presented in Table 4-8. As stated earlier turbidity is a surrogate measure of particle count and the strong correlation between effluent turbidity and effluent particle counts of 0.94 also support the fact. The DAF effluent pH varies from 6.1 to 6.6 with an average of 6.4 and standard deviation of 0.12. The results of descriptive statistical analysis are presented in Table 4-8. The correlation matrix between each variable of the study is presented in Table 4-9.

Table 4-8 Descriptive statistics of DAF pilot plant (January 2003 to February 2003).

	Mean	Std Dev	Var	Min	Max	Percentile P 0.05	P 0.50	P 0.95
pH	6.6	0.3	0.1	5.9	7.0	6.2	6.6	6.9
Flow rate (L/min)	2.0	0.3	0.1	1.8	3.6	1.8	1.8	2.4
Temp (celcius)	6	1	1	5	8	5	6	8
Alkalinity (mg/L)	4	1	1	3	5	3	4	5
Conductivity (μS/cm)	15	2	4	12	20	12	15	20
Color (TCU)	88.0	18.0	324.7	66.0	130.0	66.0	89.0	119.0
Turbidity (NTU)	0.98	0.60	0.36	0.4	3.18	0.48	0.77	2.01
Particle Count (#/mL)	3837	2797	7822970	976	11395	977	3270	9543
Alum Dose (mg/L)	53	15	239	20	90	25	52	79
Soda Ash (mg/L)	36	11	125	12	61	16	35	55
Eff pH	6.4	0.1	0.0	6.1	6.6	6.2	6.4	6.6
Eff Color (TCU)	6.9	3.3	10.7	3.0	22.0	4.0	6.0	15.2
Eff Turbidity (NTU)	0.74	0.17	0.03	0.52	1.48	0.55	0.71	1.09
Eff Part. C (#/mL)	655	396	157072	296	2345	314	548	1584

Table 4-9 Correlation matrix between the variables of pilot-scale data (January 2003 to February 2003)

	pH	Flow rate	Temp	Alk.	Cond.	Color	Turb.	pc	Alum	Soda Ash	Eff pH	Eff Color	Eff Turb.	Eff pc
pH	1													
Flow rate	-0.40	1												
Temp	-0.03	0.11	1											
Alkalinity	0.14	-0.09	-0.08	1										
Conductivity	0.28	-0.08	0.06	-0.52	1									
Color	-0.57	0.40	0.54	-0.11	-0.09	1								
Turbidity	-0.42	0.21	0.44	-0.20	-0.07	0.72	1							
Part. Count	-0.56	0.31	0.49	-0.21	-0.12	0.81	0.89	1						
Alum Dose	-0.45	0.33	0.51	-0.05	-0.11	0.84	0.71	0.73	1					
Soda Ash	-0.43	0.32	0.52	-0.01	-0.14	0.84	0.71	0.73	0.99	1				
Eff pH	0.37	-0.17	-0.21	0.66	-0.18	-0.40	-0.40	-0.44	-0.27	-0.21	1			
Eff Color	0.23	-0.15	-0.24	0.01	0.11	-0.27	-0.19	-0.26	-0.55	-0.52	0.06	1		
Eff Turbidity	-0.27	0.17	-0.06	-0.35	0.11	0.26	0.29	0.28	0.02	0.02	-0.42	0.44	1	
Eff Part. C	-0.21	0.08	-0.14	-0.24	0.04	0.16	0.20	0.17	-0.03	-0.04	-0.32	0.43	0.94	1

4.2.2 Selection of Input and Output Parameters

Data on raw water quality parameters (pH, turbidity, color, particle count, temperature, alkalinity, conductivity) and the process parameters (alum dose, soda ash dose, plant flow rate) were collected during the DAF pilot plant study and were used as input parameters. While building the model, all the input parameters that might influence the performance of the model output were considered and those found to be less important were removed in subsequent trials to ensure that the best model was obtained.

DAF effluent turbidity, color and overall particle count were measured as process performance parameters during pilot plant operation. These three parameters were probable output parameters to measure process performance while building ANN models.

Table 4-9 shows a strong correlation of 0.94 between effluent turbidity and effluent particle count. The unstable nature of the on-line particle counter in the pilot plant and the presence of fine bubbles in DAF effluent water made the on-line particle counter hard to read. Therefore, two parameters (DAF effluent turbidity and color) were chosen as output parameters.

Figure 4-28 shows the variation of DAF effluent turbidity during the pilot plant experiments. DAF effluent turbidity had an average value of 0.74 NTU with standard deviation of 0.17 NTU. The 95^{th} percentile value is 1.09 NTU. The effluent turbidity was not below 0.50 NTU as the full scale DAF effluent water quality, however, was below 1 NTU in most of the experimental runs.

Figure 4-27 shows the variation of DAF effluent color during the study. The DAF effluent color fluctuated with a mean of 6.9 TCU and a standard deviation of 3.3 TCU. The coefficient of variation of the performance parameters was 0.32 and 0.16 for the DAF effluent color and the DAF effluent turbidity, respectively. Input and output parameters selected for building the ANN model are presented in Table 4-10.

Table 4-10 Model parameters for DAF pilot study

DAF effluent color model	DAF effluent turbidity model
Temperature (^{o}C)	Alkalinity (mg/L as $CaCO_3$)
pH	Conductivity (μS/cm)
Alkalinity (mg/L as $CaCO_3$)	Color (TCU)
Conductivity (μS/cm)	Turbidity (NTU)
Turbidity (NTU)	Flow rate (m^3/hr)
Color (TCU)	Alum dose (mg/L)
Flow rate (m^3/hr)	Soda ash dose (mg/L)
Alum dose (mg/L)	
Soda ash dose (mg/L)	

4.2.3 Selection and Organization of Data Patterns

Two different ANN models were developed to predict effluent turbidity and effluent color to evaluate the performance of the DAF pilot treatment plant. The modeling data sets consisted of 84 data patterns and the outliers were detected and were removed from the data set and recorded. The data patterns were first sorted according to the output parameter and separated into the training, testing and production data sets using 3:1:1 ratio respectively. ANOVA analyses were performed on the training, testing and production data patterns to ensure that all three data sets were statistically similar with regards to the mean values for each variable. There were 50 training patterns, 17 testing patterns and 17 production patterns. A descriptive statistical analysis of the 84 data patterns used for developing the ANN models in predicting effluent color and turbidity is given in Table 4-11.

Table 4-11 Statistical analyses of data patterns for developing ANN model from DAF pilot unit

						Percentile		
	Mean	Std Dev	Var	Min	Max	P 0.05	P 0.50	P 0.95
pH	6.6	0.3	0.1	5.9	7.0	6.2	6.6	6.9
Flow rate (L/min)	2.0	0.3	0.1	1.8	2.4	1.8	1.8	2.4
Temp (celcius)	6	1	1	5	8	5	6	8
Alkalinity (mg/L)	4	1	1	3	5	3	4	5
Conductivity (µS/cm)	15	2	4	12	20	12	15	20
Color (TCU)	87.6	17.5	307.2	66.0	130.0	66.0	88.5	114.7
Turbidity (NTU)	0.96	0.59	0.35	0.40	3.18	0.48	0.77	1.98
Alum Dose (mg/L)	53	15	236	20	90	25	52	79
Soda Ash (mg/L)	36	11	124	12	61	16	35	55
Eff Color (TCU)	6.9	3.3	10.8	3.0	22.0	4.0	6.0	15.4
Eff Turbidity (NTU)	0.74	0.17	0.03	0.52	1.48	0.55	0.71	0.97

4.2.4 Architecture of the Neural Model

The three-layer multi-layer perceptron architecture using a linear scaling function in the input layer, logistic activation function in the hidden and output layers, and the back-propagation learning rule were deployed to develop the ANN models. The number of hidden layer neurons was evaluated by changing this in the range of 1 to 30. The best result was obtained using 12 neurons in the hidden layer for the color model. The turbidity model was first built using all the input parameters that were used in building color model. However, the best turbidity model was obtained using 11 hidden layer neurons and neither pH nor temperature was included as input parameters to build the model. During the model building process and sensitivity analysis pH and temperature appeared as less important parameters and were eliminated to obtain the best model. When applied to the production data set the color model demonstrated good predictive capacity with a mean absolute error of 1.2 TCU. The turbidity model demonstrated predictive capacity with a mean absolute error of 0.09 NTU when applied to the production data set. The evaluations of the best models obtained are presented in Table 4-12 for the color model and in Table 4-13 for the turbidity model.

Table 4-12 Modeling and cross validation result on color model

Data set	R^2	Mean absolute error (TCU)
Training	0.84	0.9
Testing	0.79	1.0
Production	0.84	1.2
Production (cross-validation)	0.75	1.1

Table 4-13 Modeling and cross validation result on turbidity model

Data set	R^2	Mean absolute error (NTU)
Training	0.47	0.07
Testing	0.35	0.09
Production	0.47	0.09
Production (cross-validation)	0.35	0.09

4.2.5 Model Stability Evaluation

Cross validation results on production data sets are presented in Table 4-12 and Table 4-13 for the color model and the turbidity model, respectively. The difference of mean absolute error between original model results and cross-validation model results is very small. The R^2 value for the cross-validation showed a lower value than the original production data set for both the models, and the mean absolute error of the cross-validated model showed a little lower value. However, the deviation between original model results and cross-validated model results were not statistically significant (95% confidence interval).

Only 84 data patterns were used to build the model. Therefore, the results showed in Figure 4-29 for the color model and Figure 4-32 for the turbidity model consist of all the data patterns (in order of testing, training and production data patterns). The results for the color removal model from DAF pilot plant are depicted graphically in Figure 4-29. The residual plot for predicting pilot DAF effluent color (TCU) is presented in

Figure 4-30. The distribution of absolute error for color model is presented in Figure 4-31.The results for the turbidity removal model are presented graphically in Figure 4-32 and the residual plot predicting DAF effluent turbidity for the whole data patterns are presented in Figure 4-33. The distribution of absolute error for turbidity model is presented in Figure 4-34.

4.3 Bench-Scale DAF

4.3.1 Source Data Analysis

The first bench-scale study was conducted at the University of Alberta premises at room temperature using different raw water color from Port Hardy. A second bench study was also conducted at Port Hardy water treatment plant using different raw water characteristics. A total number of 210 data patterns were collected during the study. The data record represents water quality and operational data. The data were fully characterized and detailed statistical analyses were performed using Microsoft Excel 2000. Scatter plots of each variable was used to detect outlier values.

The raw water quality parameters were color, turbidity, particle count, pH, temperature, conductivity, and alkalinity. The raw water color varied from 35 TCU to 190 TCU. The average raw water color during the study was 112 TCU with a standard deviation of 59.5 TCU. Raw water turbidity ranges from 0.38 NTU to 1.49 NTU, with a mean of 0.88 NTU and standard deviation of 0.41 NTU. The maximum raw water color

of 190 TCU was obtained during a winter storm event in the month of December. This high color was collected in a container and shipped to the University of Alberta, Edmonton. The raw water particle count varies from 976 number/mL and 7,649 number/mL with an average value of 3,387 number/mL and standard deviation of 2,174 number/mL. Other raw water parameters such as temperature, alkalinity, conductivity, pH varied from 5°C to 21°C with an average of 14°C and standard deviation of 8°C; 3 mg/L to 9 mg/L as $CaCO_3$, with an average of 6 mg/L and standard deviation of 2 mg/L as $CaCO_3$; 14 μS/cm to 20 μS/cm with an average of 16 μS/cm and standard deviation of 1 μS/cm; and 6.2 to 6.9 respectively. Raw water temperature over the study is presented in Figure 4-35. Variation of raw water pH, alkalinity, and conductivity are presented in Figure 4-36, Figure 4-37, and Figure 4-38, respectively. Variations of raw water color and turbidity are presented in Figure 4-39, and Figure 4-40, respectively.

During the bench-scale study the alum dose varied from 10 mg/L to 120 mg/L; while the soda ash dosing rate varied from 0 mg/L to 120 mg/L. The strong correlation was also found between alum dose and soda ash dose of 0.95, alum and raw water color of 0.66, soda ash and raw water color of 0.70. These strong correlations suggest the dependence of coagulant and chemical dose on raw water color. The alum dose and soda ash dose are presented in Figure 4-41 and Figure 4-42 respectively. The bench-scale DAF effluent turbidity varied from 0.28 NTU to 9.80 NTU with an average of 1.28 NTU and standard deviation of 1.60 NTU. The effluent color varied from 3 TCU to 136 TCU. The effluent particle varied from 121 number/mL to 20,302 number/mL with an average value of 1,643 number/mL and standard deviation of 2,888 number/mL. The results of

descriptive statistical analysis are presented in Table 4-14. The correlation matrix between each variable of the study is presented in Table 4-15.

Table 4-14 Descriptive statistics of DAF bench study

	Mean	Std Dev	Var	Min	Max	P 0.05	Percentile P 0.50	P 0.95
pH	6.6	0.2	0.0	6.2	6.9	6.2	6.7	6.8
Temp	14	8	56	5	21	5	21	21
Alkalinity	6	2	4	3	9	3	7	9
Conductivity	16	1	2	14	20	14	15	16
Color	112.4	59.5	3538.8	35.0	190.0	35.0	100.0	190.0
Turbidity	0.88	0.41	0.17	0.38	1.49	0.40	0.89	1.31
Particle Count	3387	2174	4727316	976	7469	996	3346	6034
Alum Dose	52	30	885	10	120	10	50	110
Soda Ash	36	25	616	0	120	5	32	84
Eff Color	14.2	17.6	309.3	3.0	136.0	3.0	9.0	41.2
Eff Turbidity	1.28	1.60	2.55	0.28	9.80	0.31	0.70	4.11
Eff Part. C	1643	2888	8340643	121	20302	213	542	7905

Table 4-15 Correlation matrix between the variables at bench-scale study

	pH	Temp	Alk.	Cond.	Color	Turb	PC	Alum	Soda Ash	Eff. Color	Eff. Turbidity	Eff PC
pH	1.00											
Temp	-0.26	1.00										
Alkalinity	-0.01	0.89	1.00									
Conductivity	0.28	-0.10	-0.21	1.00								
Color	-0.57	0.42	0.10	-0.34	1.00							
Turbidity	-0.55	0.30	-0.04	0.02	0.86	1.00						
Particle Count	-0.64	0.28	-0.05	0.00	0.83	0.98	1.00					
Alum Dose	-0.38	0.12	-0.08	-0.18	0.66	0.65	0.61	1.00				
Soda Ash	-0.41	0.18	-0.04	-0.21	0.70	0.67	0.63	0.95	1.00			
Eff Color	-0.13	0.27	0.20	-0.14	0.28	0.18	0.18	-0.37	-0.30	1.00		
Eff Turbidity	-0.10	0.41	0.37	-0.07	0.16	0.09	0.09	-0.20	-0.24	0.58	1.00	
Eff Part. C	-0.05	0.28	0.27	-0.06	0.08	0.02	0.02	-0.15	-0.21	0.48	0.82	1.00

4.3.2 Selection of Input and Output Parameters

Raw water pH, turbidity, color, particle count, DOC, UV_{254}, temperature, alkalinity, conductivity; and the process parameters such as alum dose, soda ash dose

were measured during the bench-scale study. DOC and UV_{254} were measured occasionally. However, the data included raw water quality parameters such as temperature, pH, turbidity, conductivity, color, alkalinity; process parameters such as alum dose, soda ash dose. DAF effluent turbidity, color, and overall particle count were measured as process performance parameters during bench-scale study. ANN model was developed using effluent turbidity and effluent color. Table 4-15 shows strong correlation of 0.82 between effluent turbidity and effluent particle count. Therefore, two parameters such as DAF effluent turbidity and color were chosen as output parameters. Figure 4-43 shows the variation of DAF effluent color during the experiments. Figure 4-44 shows the variation of DAF effluent turbidity during the study. Selected input and output parameters for building ANN model are presented below at Table 4-16.

Table 4-16 Model parameters for bench-scale DAF

DAF effluent color model	DAF effluent turbidity model
Temperature (°C)	Temperature (°C)
pH	pH
Alkalinity (mg/L as $CaCO_3$)	Alkalinity (mg/L as $CaCO_3$)
Conductivity (μS/cm)	Conductivity (μS/cm)
Color (TCU)	Color (TCU)
Turbidity (NTU)	Turbidity (NTU)
Alum dose (mg/L)	Alum dose (mg/L)
Soda ash dose (mg/L)	Soda ash dose (mg/L)

4.3.3 Selection and Organizations of Data Patterns

The modeling data sets consisted of 195 data patterns after the questionable data patterns were removed and recorded. During the data analysis, 10 data patterns were detected as outliers, which is less than 4% of the total data patterns. ANN models were developed to predict effluent turbidity and effluent color to evaluate the performance of the DAF jar tester. The data patterns were first sorted according to the output parameter and separated into the training, testing and production data sets using 3:1:1 ratio and analysis of variance was performed on each data set to ensured that all three data sets are statistically similar with regards to the mean values for each variable. There were 117 training patterns, 39 testing patterns and 39 production patterns. A descriptive statistical analysis of the 195 data patterns for developing the ANN models for predicting effluent color and turbidity is given in Table 4.17.

Table 4-17 Statistical analyses of model data patterns for DAF bench-scale study

						Percentile		
	Mean	Std Dev	Var	Min	Max	P 0.05	P 0.50	P 0.95
pH	6.6	0.2	0.0	6.2	6.9	6.2	6.7	6.8
Temp (celcius)	13	8	56	5	21	5	8	21
Alkalinity (mg/L)	6	2	4	3	9	3	5	9
Conductivity(μS/cm)	16	1	2	14	20	14	15	17
Color (TCU)	112.0	57.9	3347.8	35.0	190.0	35.0	100.0	190.0
Turbidity (NTU)	0.88	0.40	0.16	0.38	1.49	0.40	0.89	1.31
Alum Dose (mg/L)	53	29	856	10	120	10	50	110
Soda Ash (mg/L)	37	25	622	0	120	5	33	85
Eff Color (TCU)	12.4	13.9	192.7	3.0	93.0	3.0	8.0	32.0
Eff Turbidity (NTU)	0.94	0.81	0.65	0.28	4.50	0.31	0.60	3.00

4.3.4 Architecture of the Neural Model

The three-layer multi-layer perceptron architecture using a scaling linear function in the input layer, logistic activation function in the hidden and output layers, and the back-propagation learning rule were deployed to develop ANN model in bench-scale study. The number of hidden layer neurons was evaluated by changing this in the range of 1 to 40. The best result was obtained using 11 neurons in the hidden layer for the color model and 12 neurons in the hidden layer for the turbidity model. When applied to the production data set the color model demonstrated predictive capacity with a mean absolute error of 3.0 TCU. The turbidity model demonstrated predicted capacity with a mean absolute error of 0.28 NTU. The evaluation of the best models obtained is presented in Table 4-18 for color model and in Table 4-19 for turbidity model.

Table 4-18 Modeling and cross validation result on color model

Data set	R^2	Mean absolute error (TCU)
Training	0.81	3.5
Testing	0.88	3.0
Production	0.91	3.0
Production (cross-validation)	0.85	3.4

Table 4-19 Modeling and cross validation result on turbidity model

Data set	R^2	Mean absolute error (NTU)
Training	0.72	0.28
Testing	0.74	0.26
Production	0.75	0.28
Production (cross-validation)	0.73	0.27

4.3.5 Model Stability Evaluation

Cross validation results on production data sets are presented in Table 4-18 and Table 4-19 for color model and turbidity model respectively. The difference of mean absolute error between original model results and cross-validation model results is small for both the models. The R^2 value is lower than the original color model production data pattern, and the mean absolute error of the cross-validated model shows a little higher value for the color model. However, the deviation between original model results and cross-validated model results are not statistically significant (95% confidence interval).

There were only 195 data patterns to build the model. The results for the color removal model from bench-scale DAF are depicted graphically in Figure 4-45. The residual plot vs. predicted pilot DAF effluent color (TCU) for the production set data patterns are presented in Figure 4-46. Distribution of absolute error for the bench-scale DAF color model is presented in Figure 4-47. The results for the turbidity removal model are presented graphically in Figure 4-48 and the residual plot vs. predicted DAF effluent

turbidity for the production data patterns are presented in Figure 4-49. The distribution of absolute error for the bench-scale DAF turbidity model is presented in Figure 4-50.

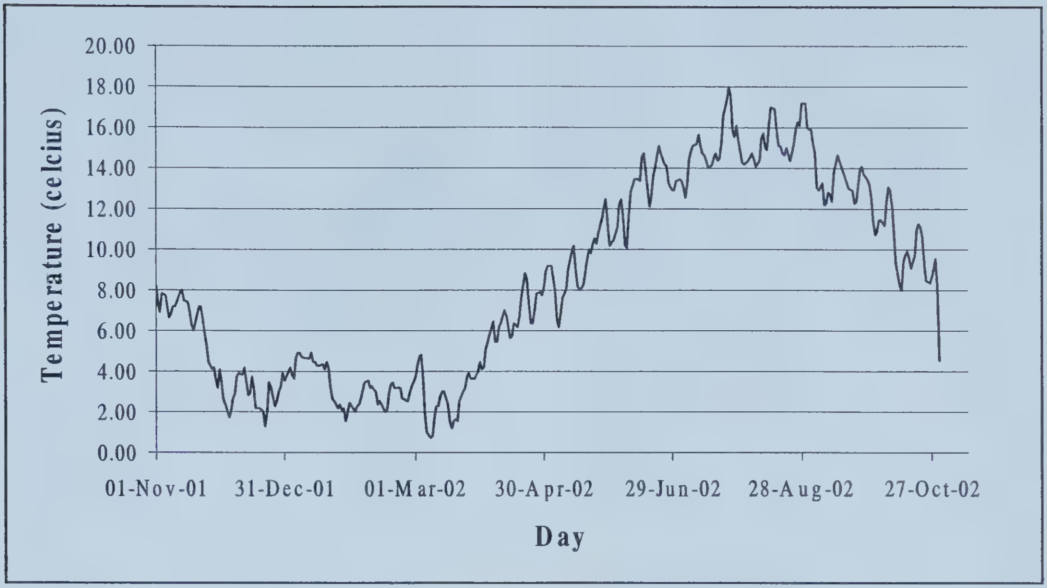

Figure 4-1 Port Hardy WTP, raw water daily average temperature, Nov. 2001-Oct. 2002.

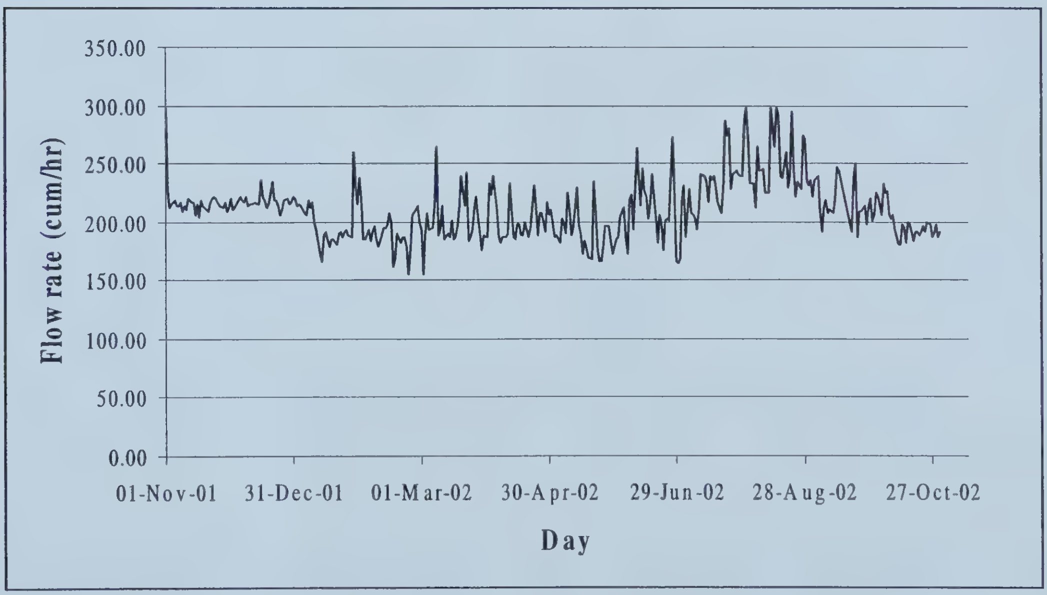

Figure 4-2 Port Hardy WTP, raw water daily average flow rate, Nov. 2001-Oct. 2002.

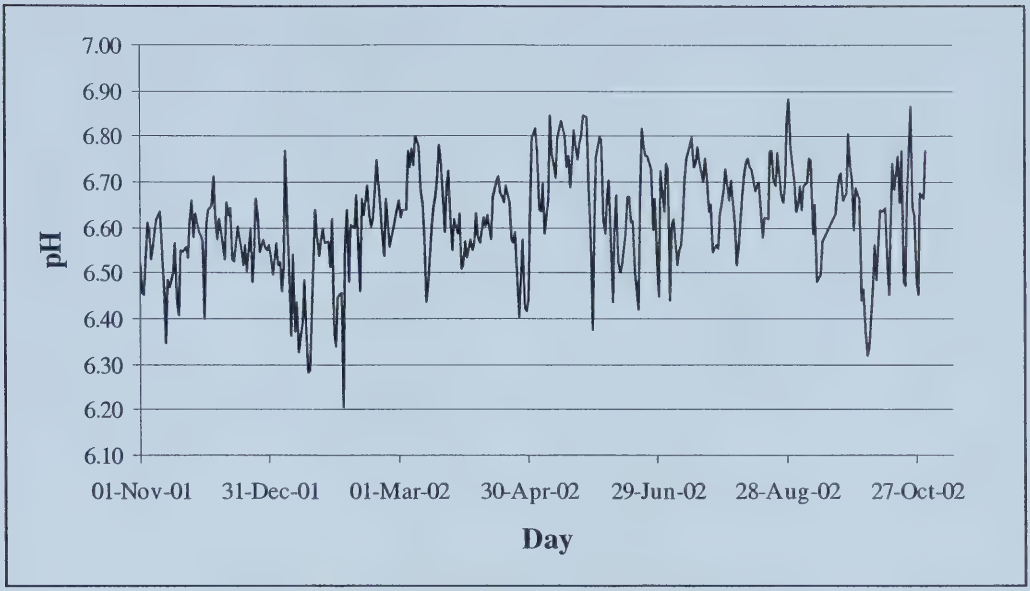

Figure 4-3 Port Hardy WTP, raw water daily average pH, Nov. 2001-Oct. 2002.

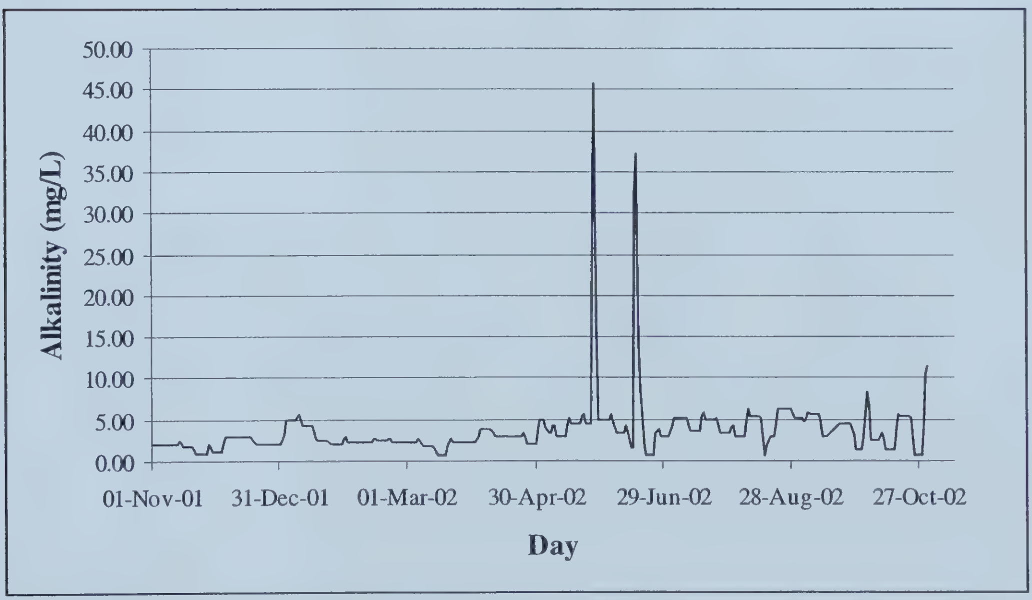

Figure 4-4 Port Hardy WTP, raw water daily average alkalinity, Nov. 2001-Oct. 2002.

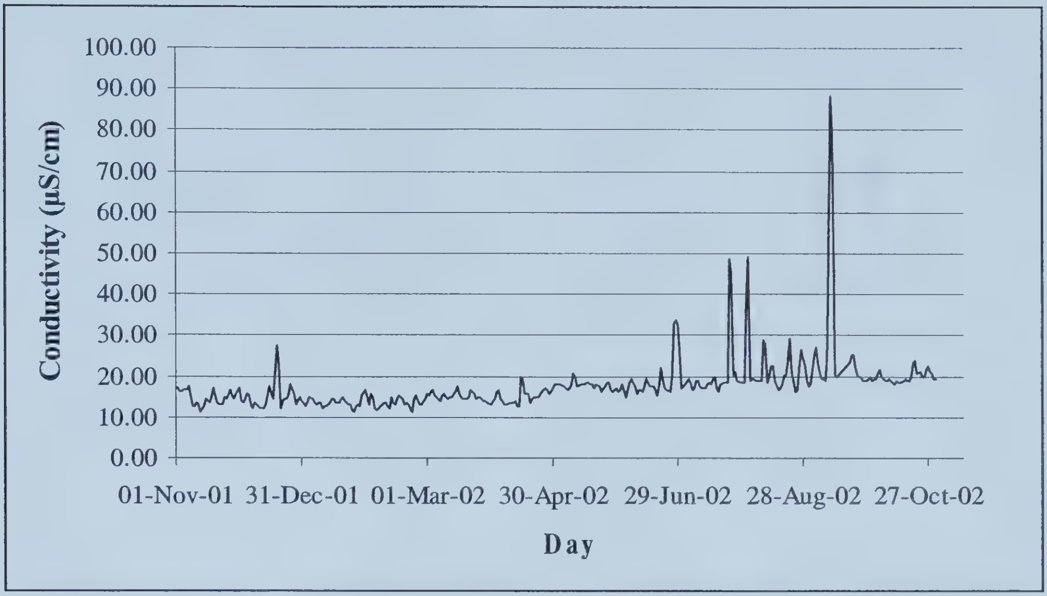

Figure 4-5 Port Hardy WTP, raw water daily average conductivity, Nov. 2001-Oct. 2002.

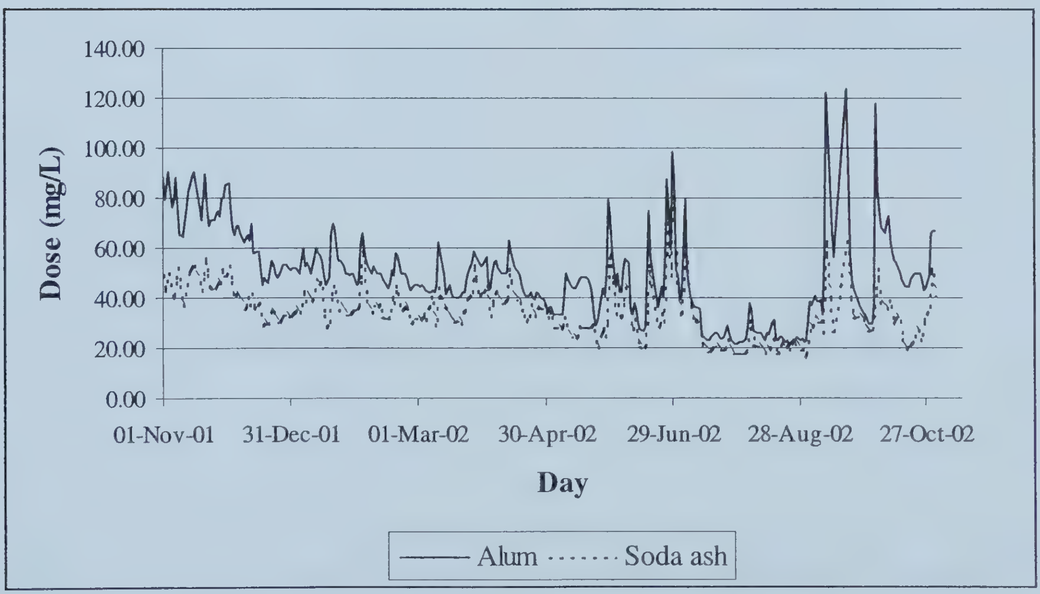

Figure 4-6 Port Hardy WTP, daily average chemical dosages, Nov. 2001-Oct. 2002.

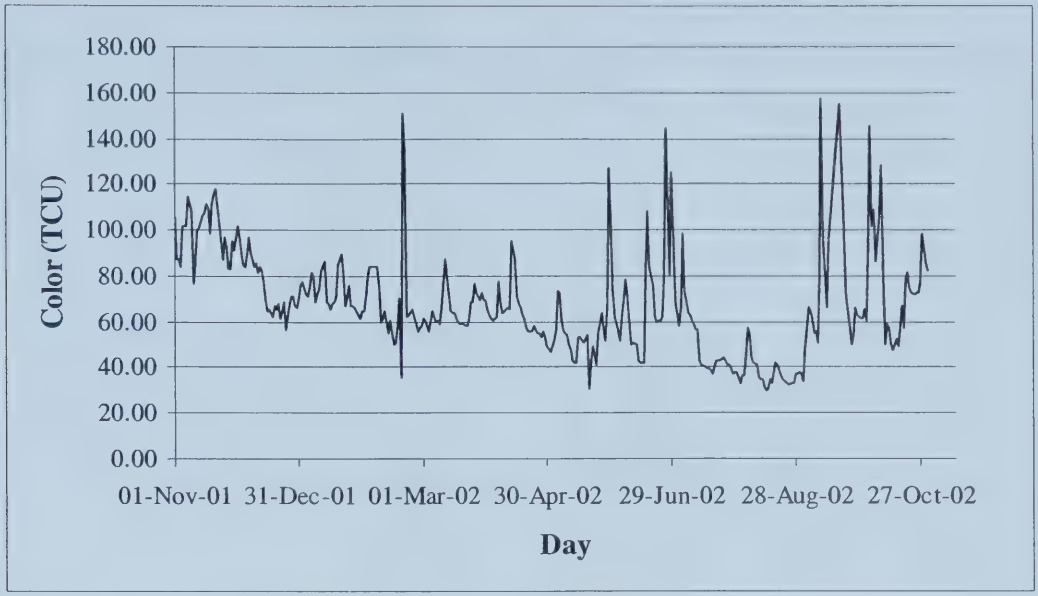

Figure 4-7 Port Hardy WTP, raw water daily average color, Nov. 2001-Oct. 2002.

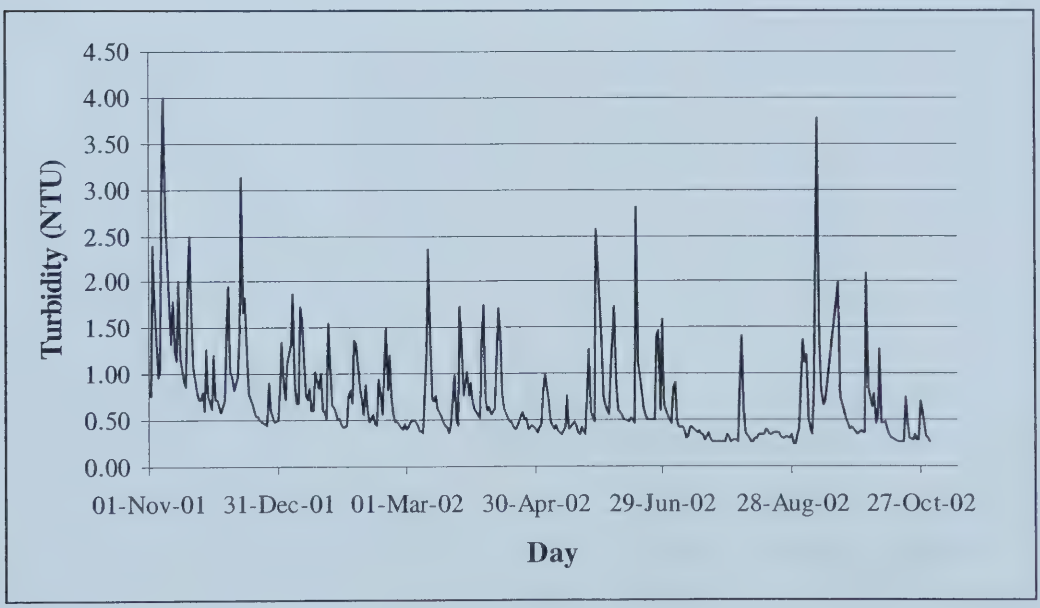

Figure 4-8 Port Hardy WTP, raw water daily average turbidity, Nov. 2001-Oct. 2002.

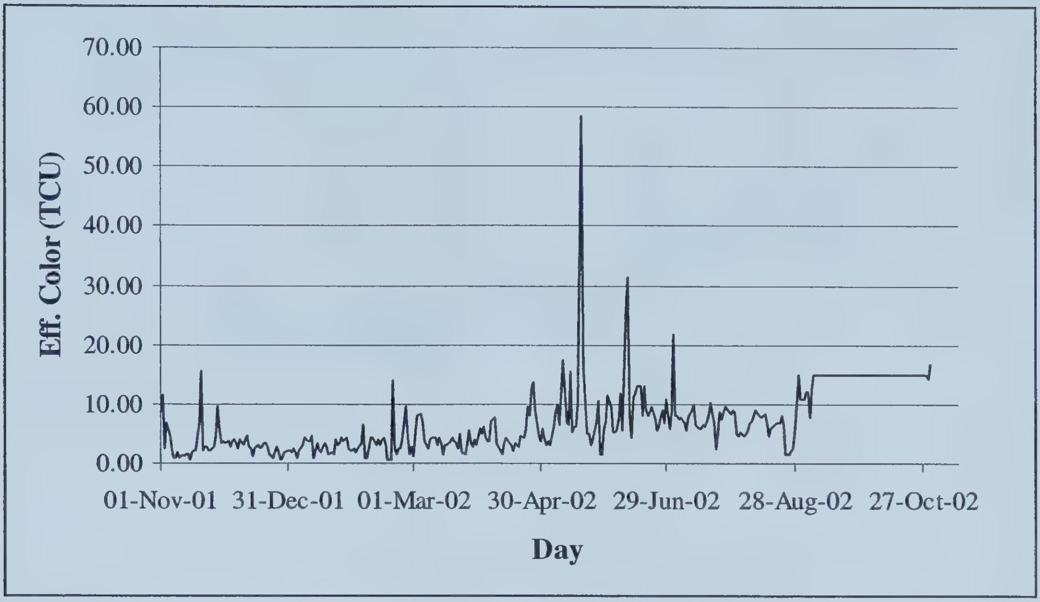

Figure 4-9 Port Hardy WTP, DAF effluent daily average color, Nov. 2001-Oct. 2002.

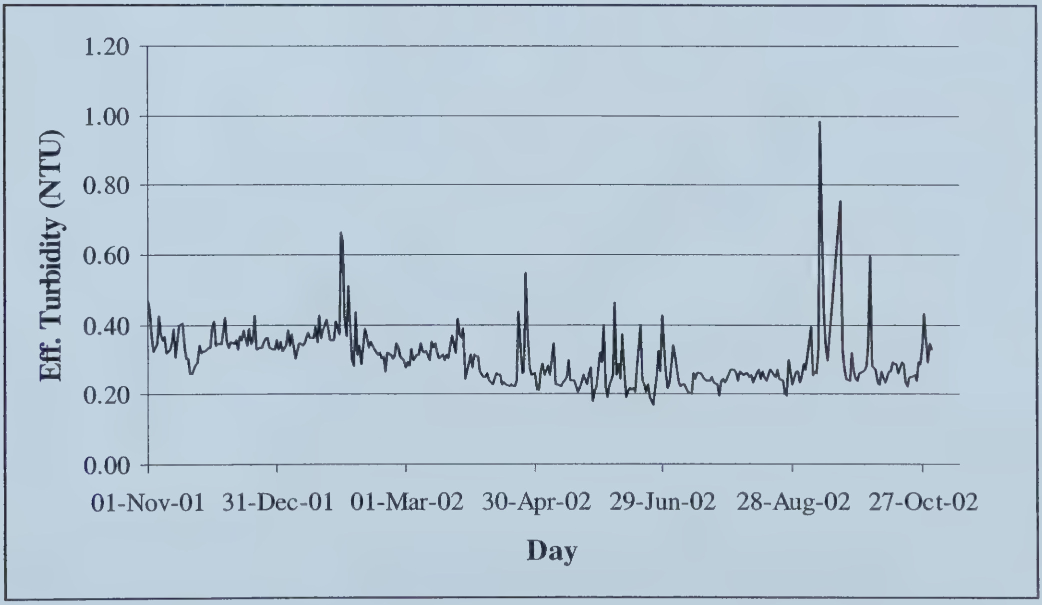

Figure 4-10 Port Hardy WTP, DAF effluent daily average turbidity, Nov. 2001-Oct. 2002.

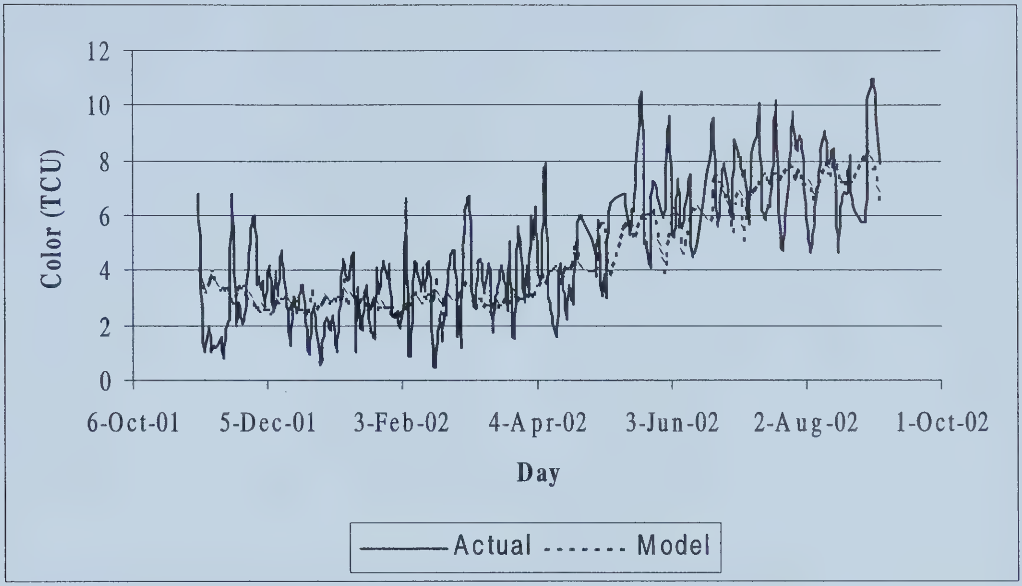

Figure 4-11 Color model results for all data patterns in full-scale DAF.

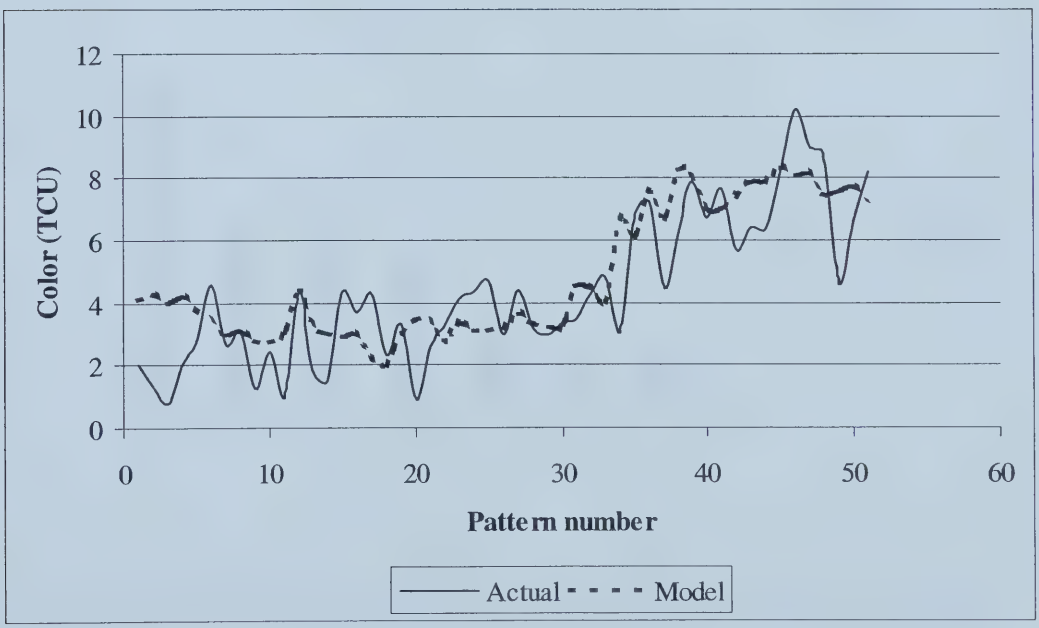

Figure 4-12 Color model results for production data patterns in full-scale DAF.

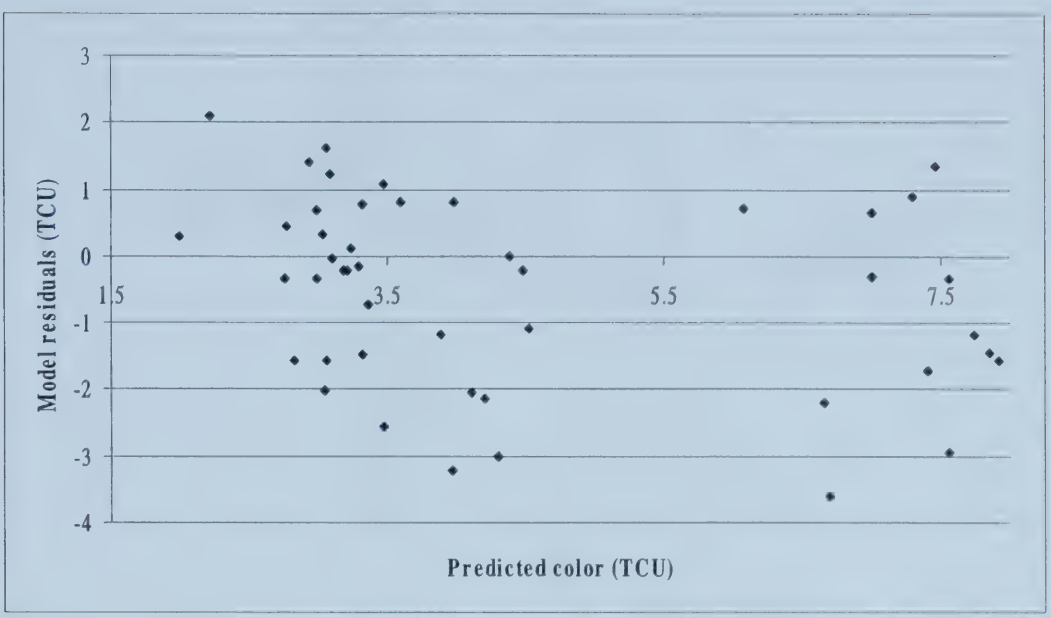

Figure 4-13 Color model residuals for the production data set.

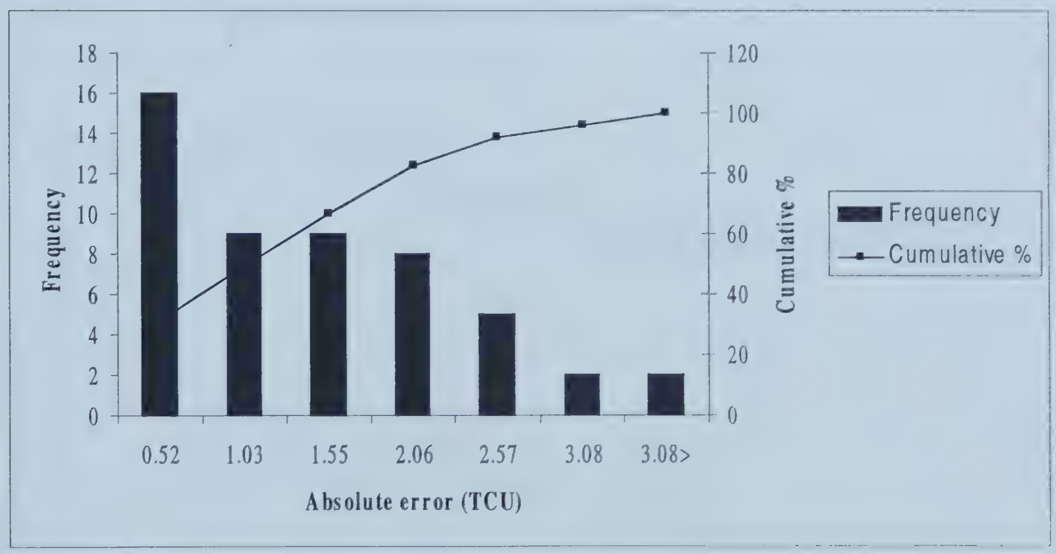

Figure 4-14 Distribution of absolute error for production data patterns of color model.

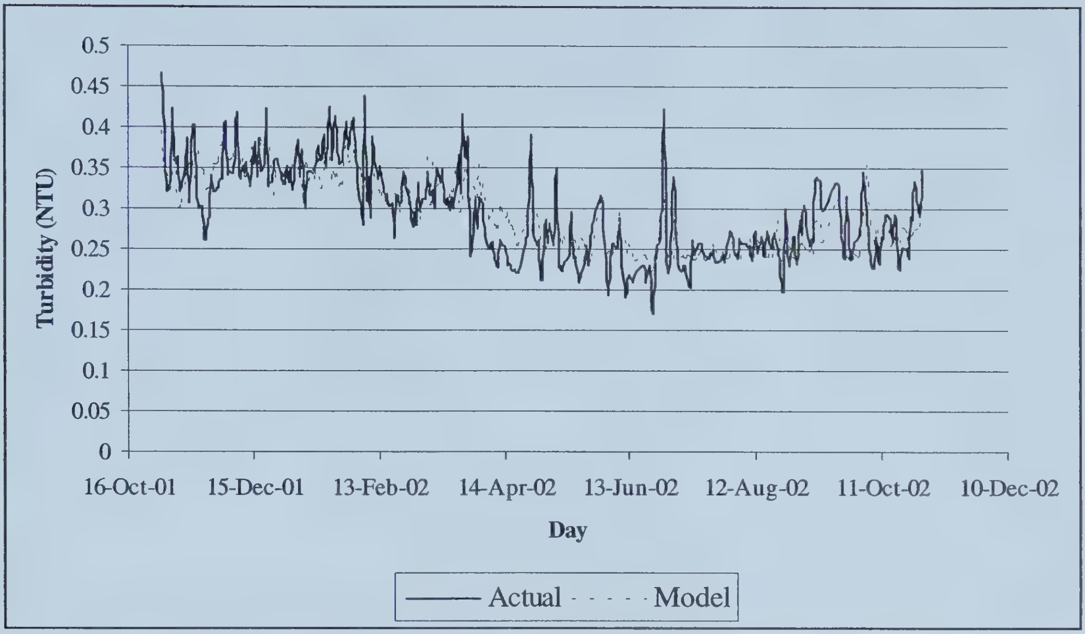

Figure 4-15 Turbidity model results for all data patterns in full-scale DAF.

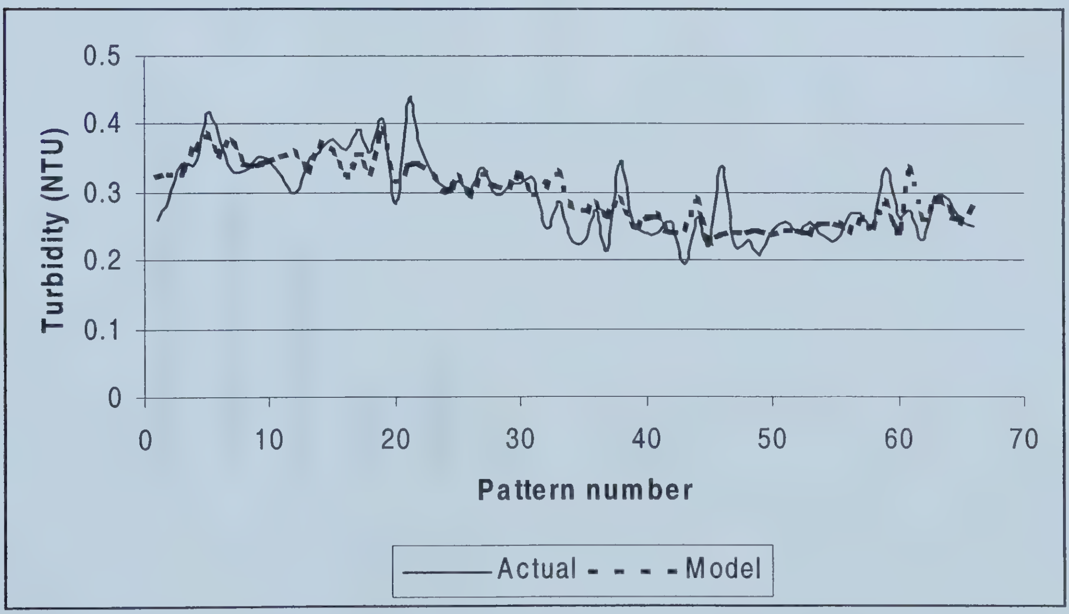

Figure 4-16 Turbidity model results for production data patterns in full-scale DAF.

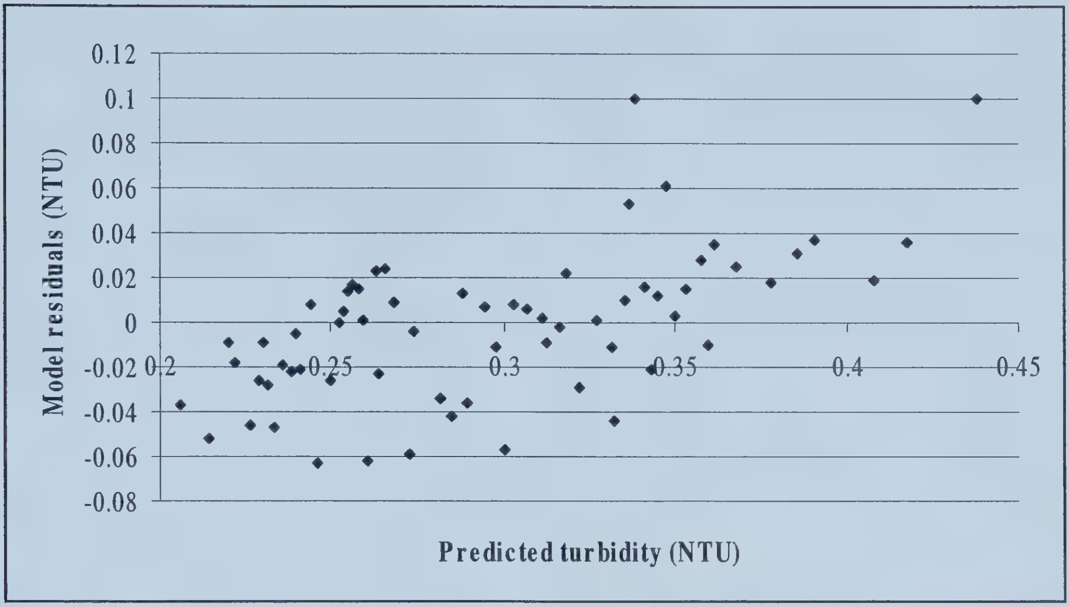

Figure 4-17 Turbidity model residuals for the production data set.

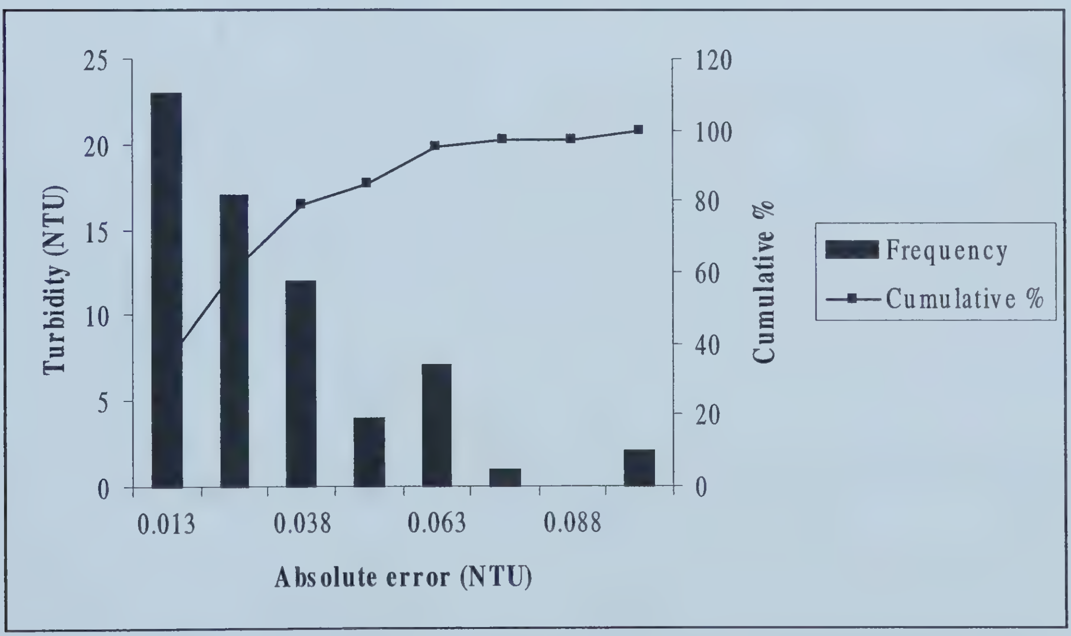

Figure 4-18 Distribution of absolute error for production data patterns of turbidity model.

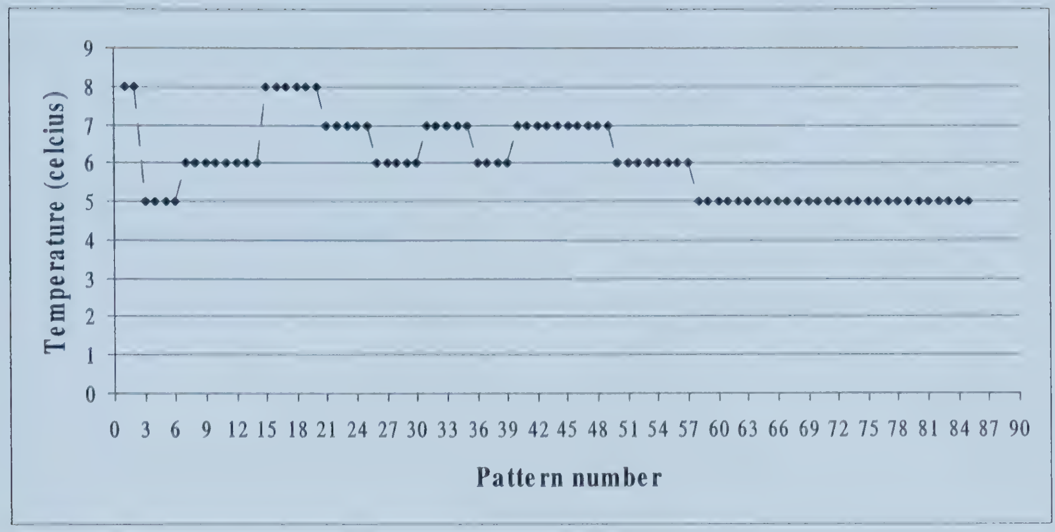

Figure 4-19 DAF pilot study, raw water temperature, January 2003-February 2003.

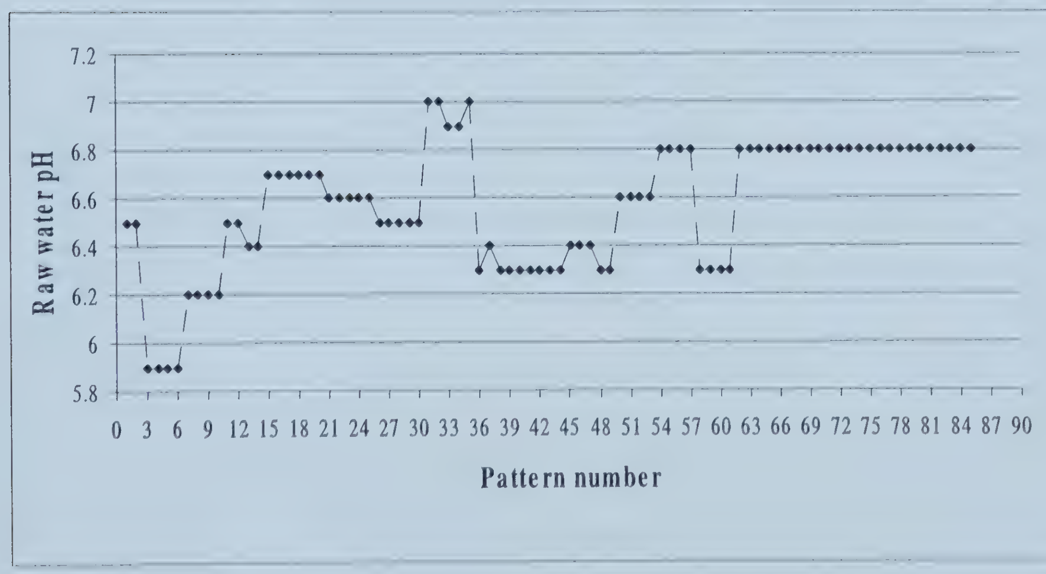

Figure 4-20 DAF pilot study, raw water pH, January 2003-February 2003.

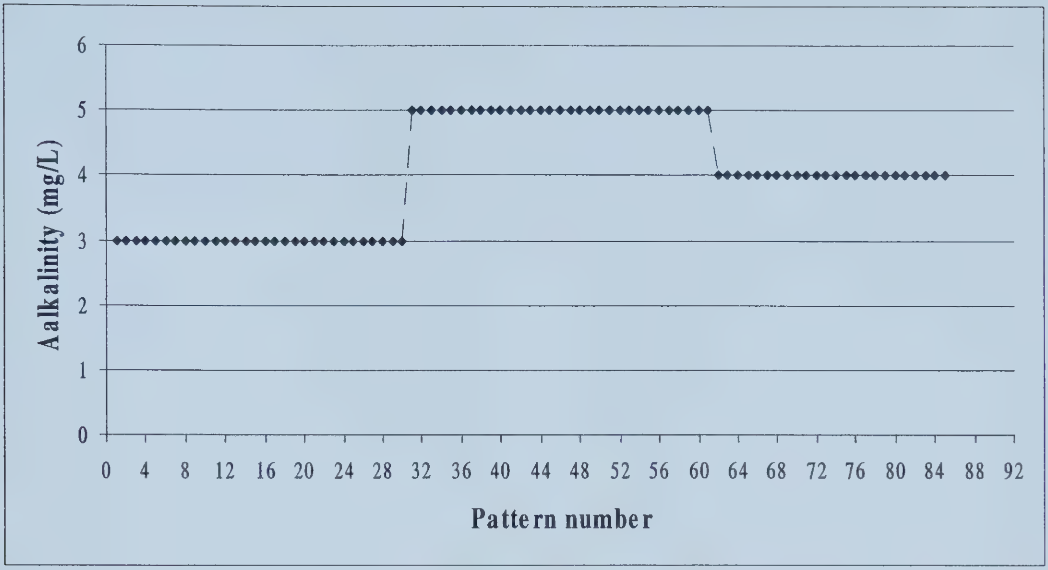

Figure 4-21 DAF pilot study, raw water alkalinity, January 2003-February 2003.

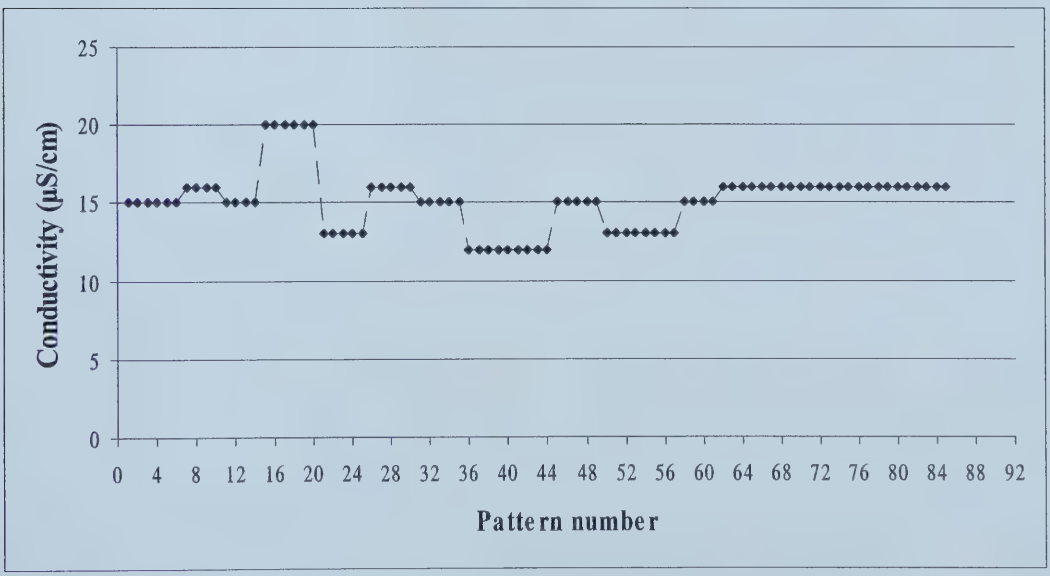

Figure 4-22 DAF pilot study, raw water conductivity, January 2003-February 2003.

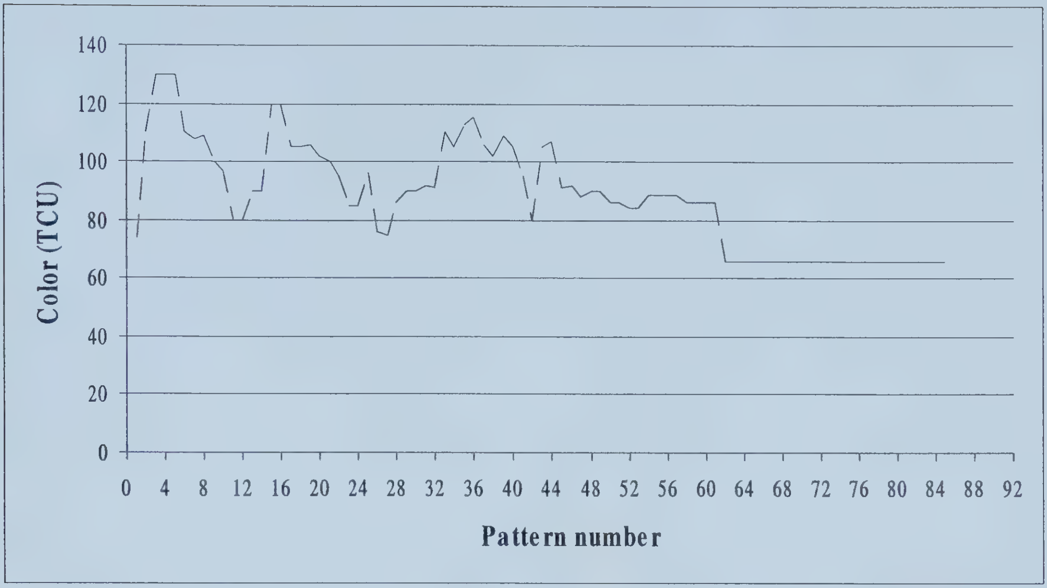

Figure 4-23 DAF pilot study, raw water color, January 2003-February 2003.

Figure 4-24 DAF pilot study, raw water turbidity, January 2003-February 2003.

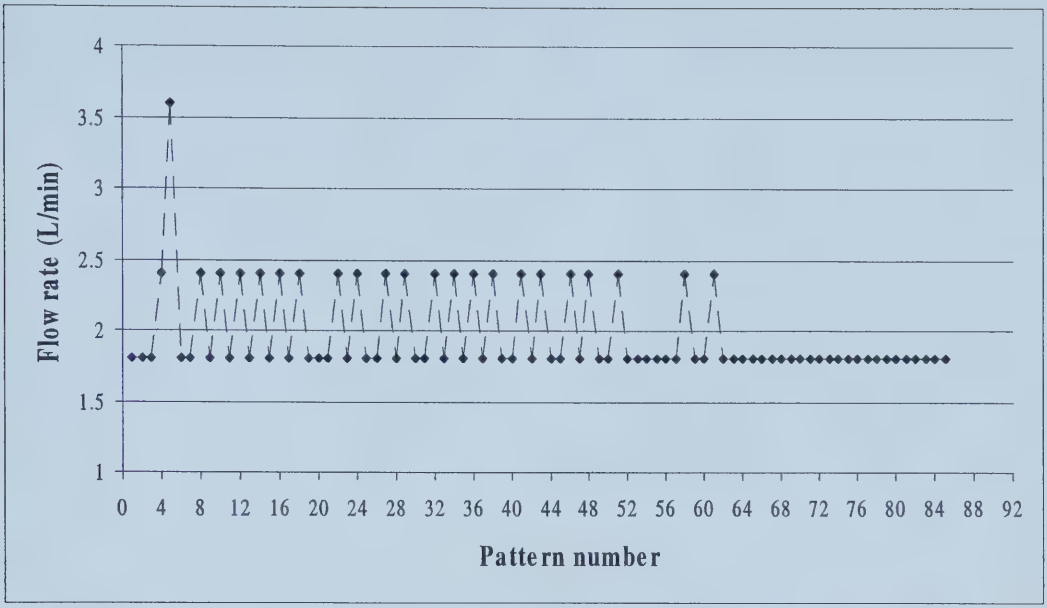

Figure 4-25 DAF pilot study, plant flow rate, January 2003-February 2003.

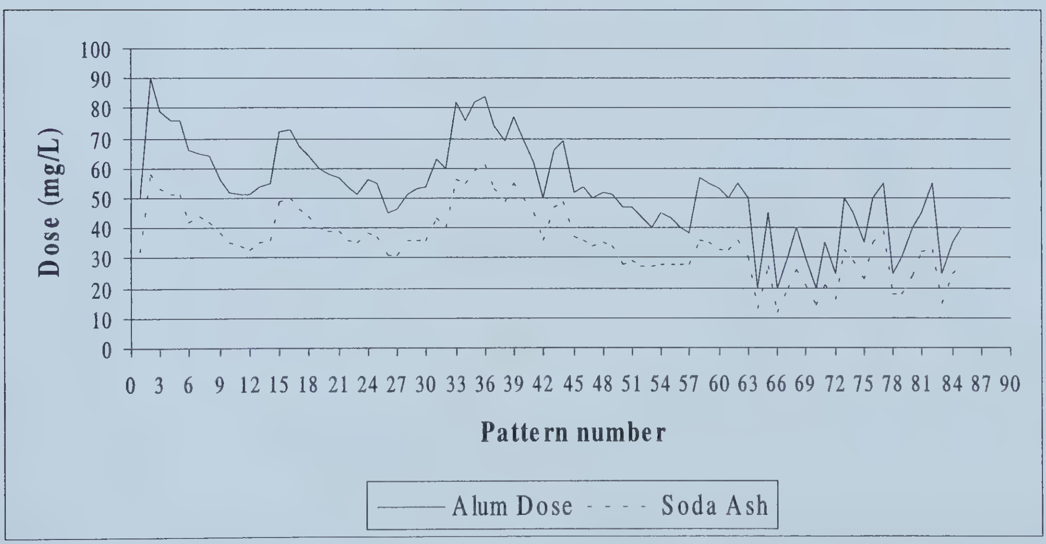

Figure 4-26 DAF pilot study, chemical dose, January 2003-February 2003.

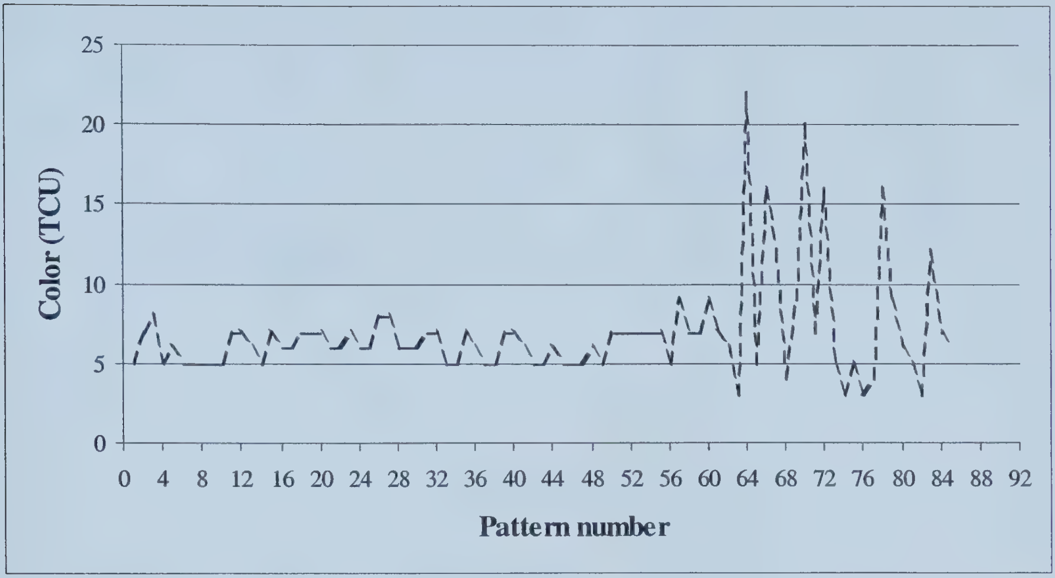

Figure 4-27 DAF pilot study, effluent color, January 2003-February 2003.

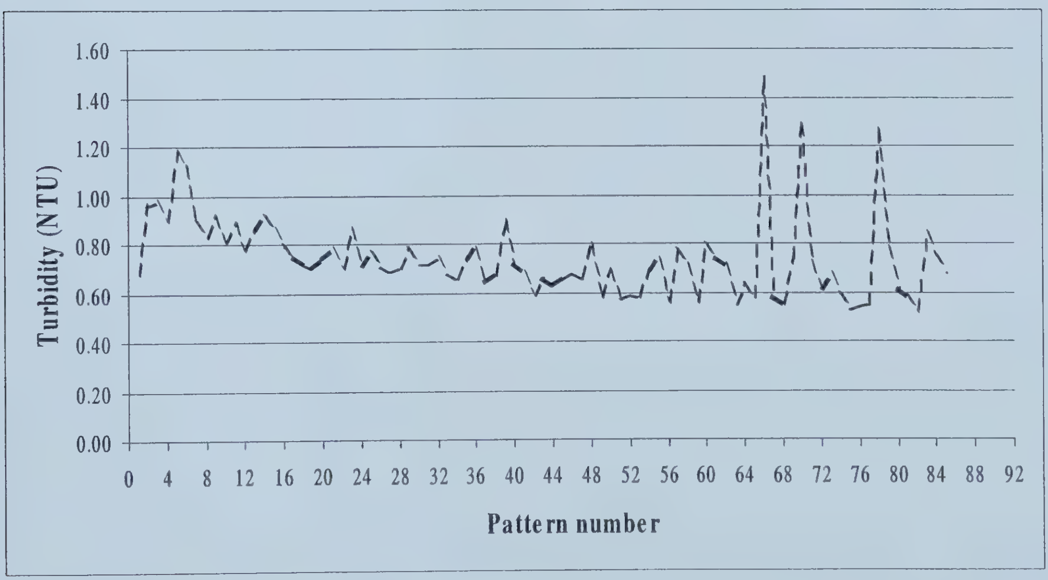

Figure 4-28 DAF pilot study, effluent turbidity, January 2003-February 2003.

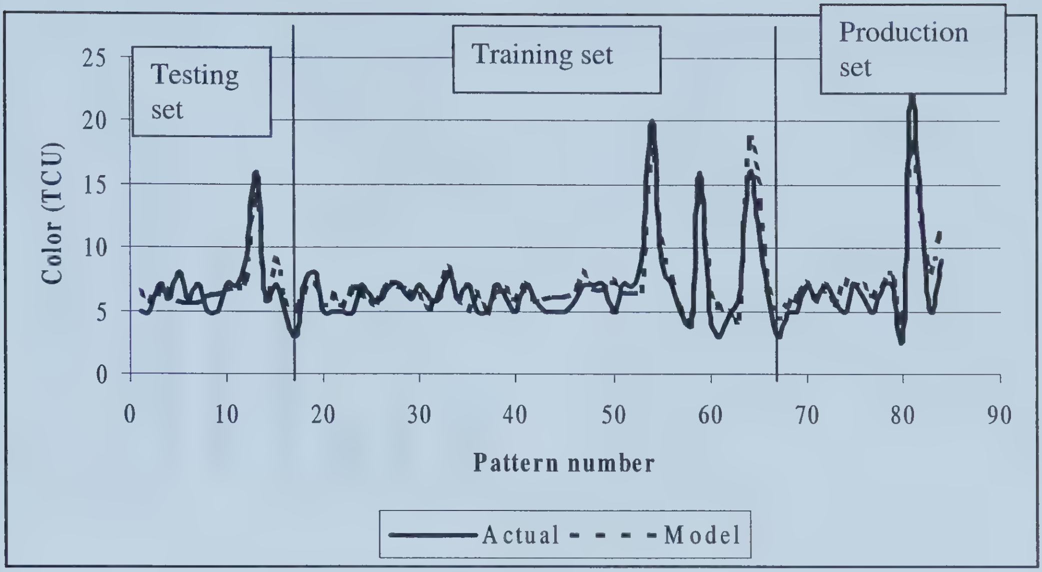

Figure 4-29 Color model results for pilot DAF.

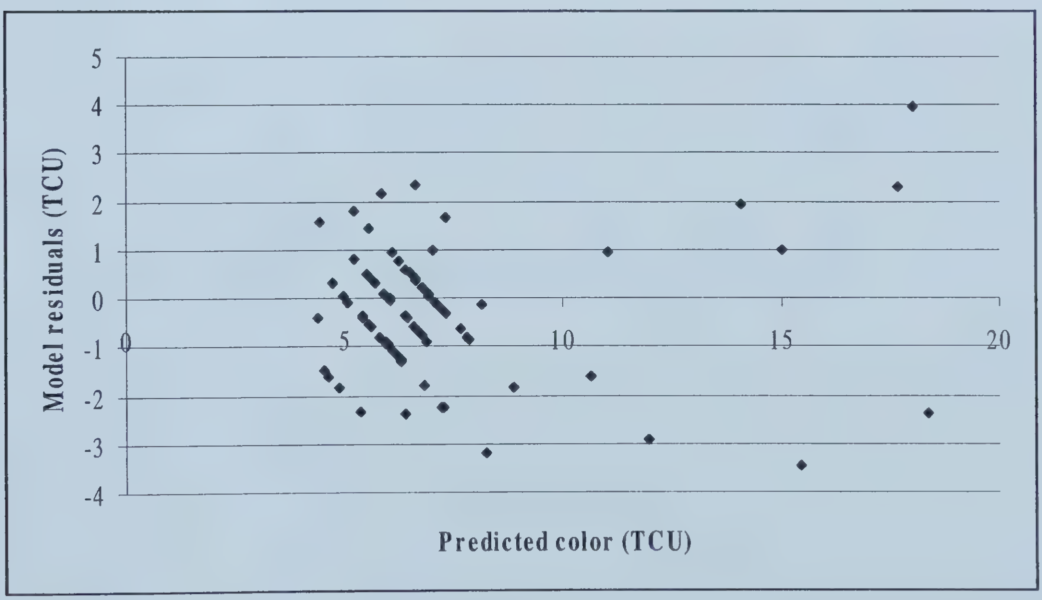

Figure 4-30 Residuals plot for the color model for pilot DAF.

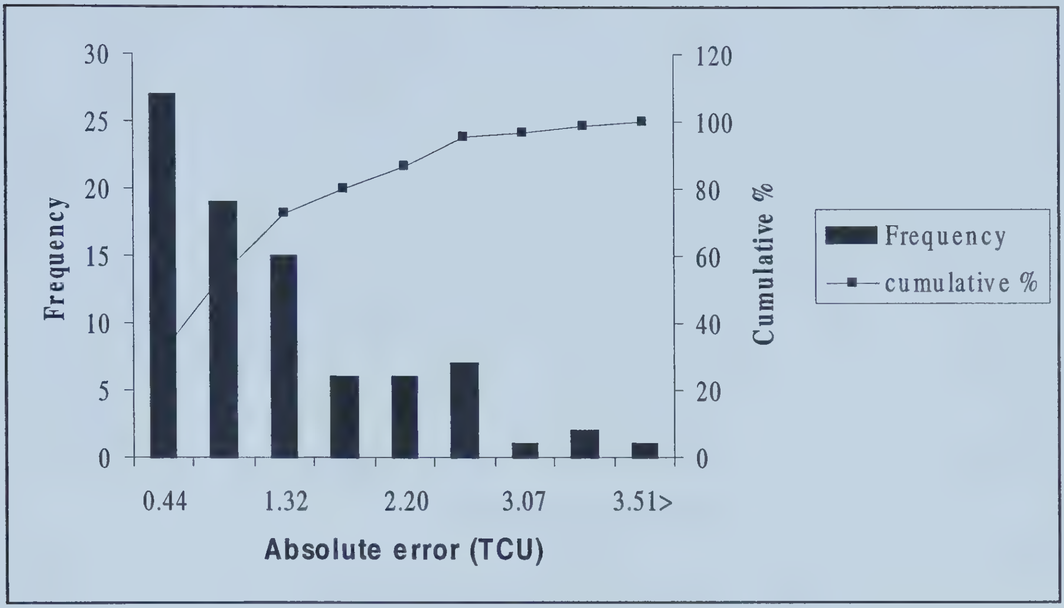

Figure 4-31 Distribution of absolute error for the pilot-scale DAF color model.

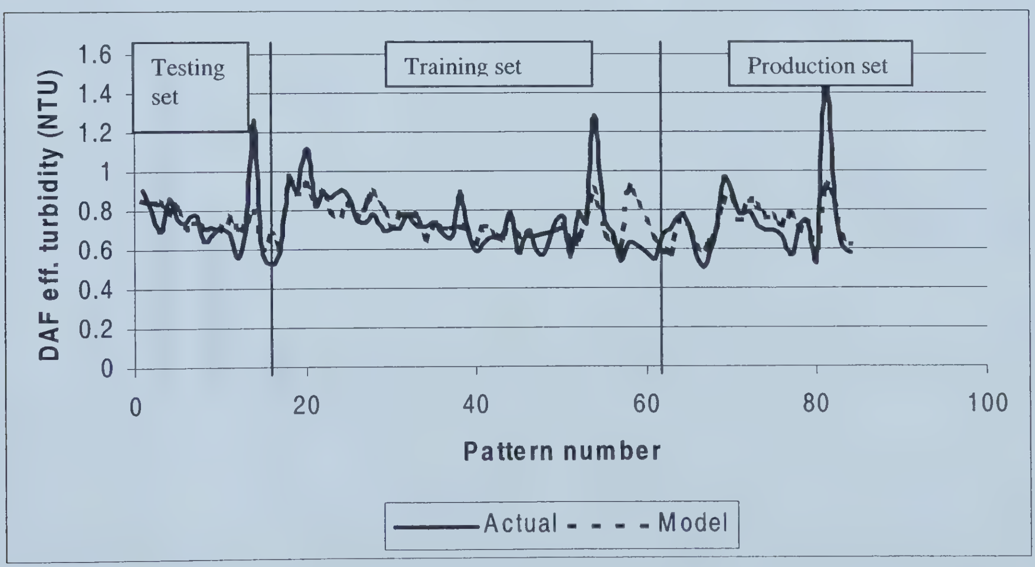

Figure 4-32 Turbidity model results for the pilot-scale DAF.

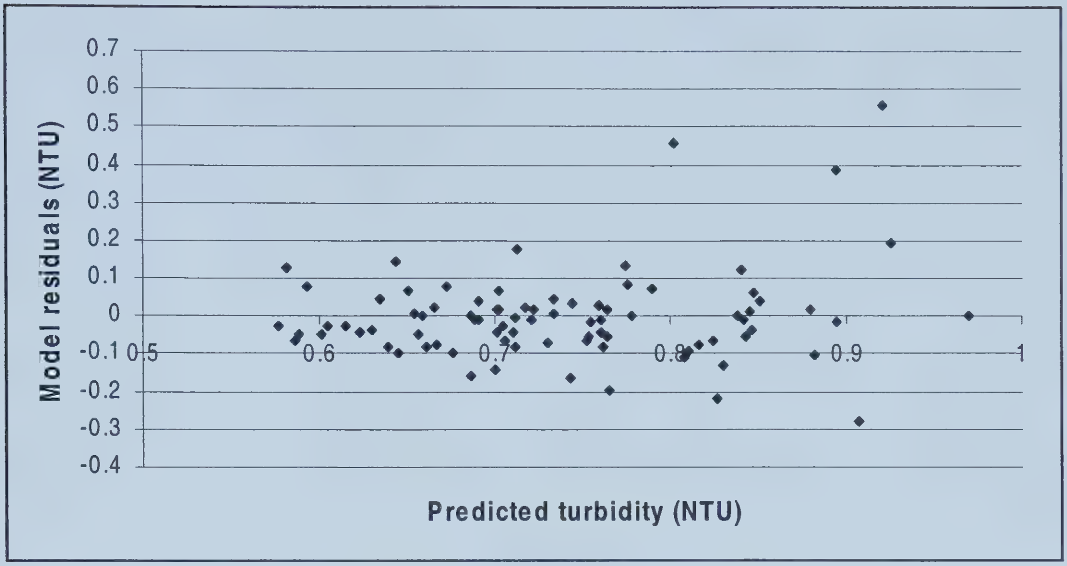

Figure 4-33 Residuals plot for the pilot-scale DAF turbidity model.

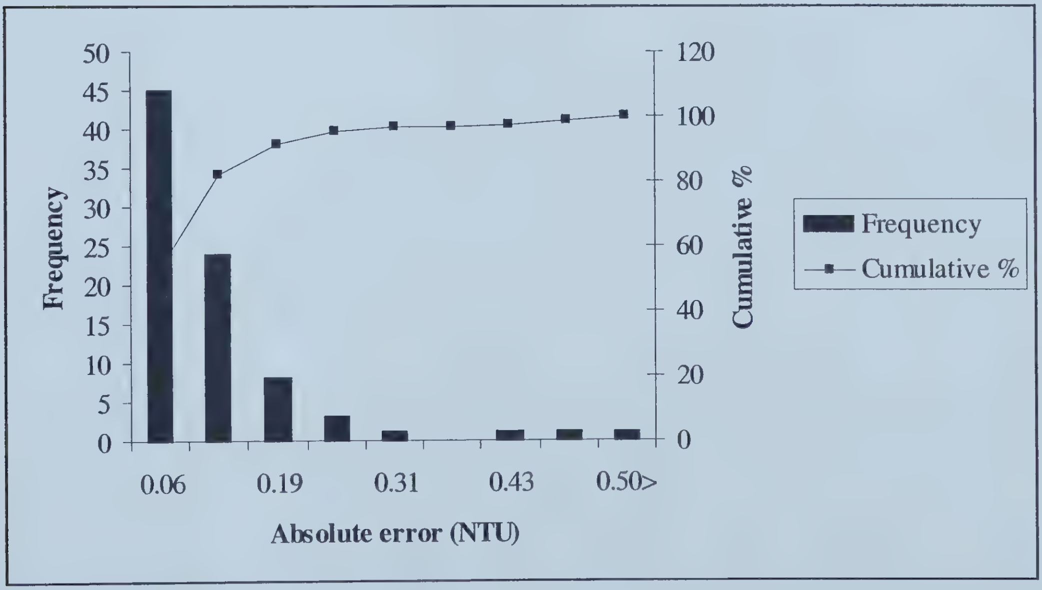

Figure 4-34 Distribution of absolute error for the pilot-scale DAF turbidity model.

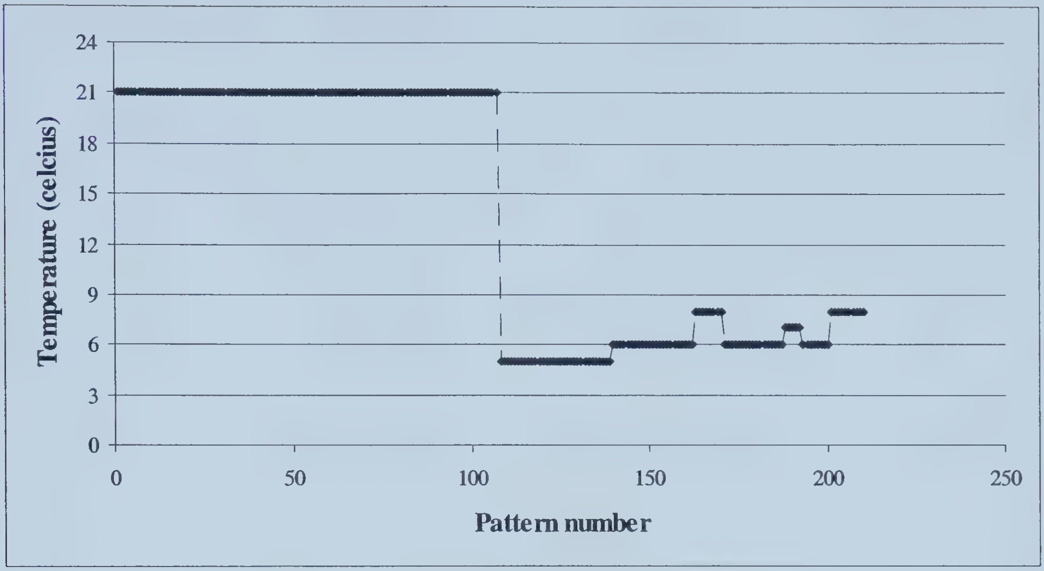

Figure 4-35 DAF bench-scale study, raw water temperature.

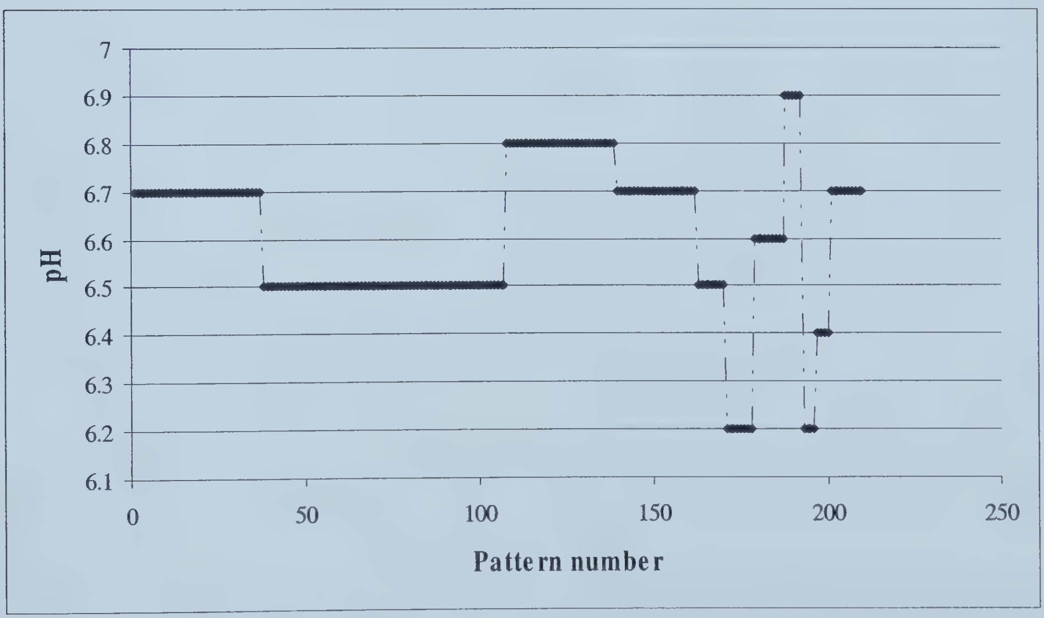

Figure 4-36 DAF bench-scale study, raw water pH.

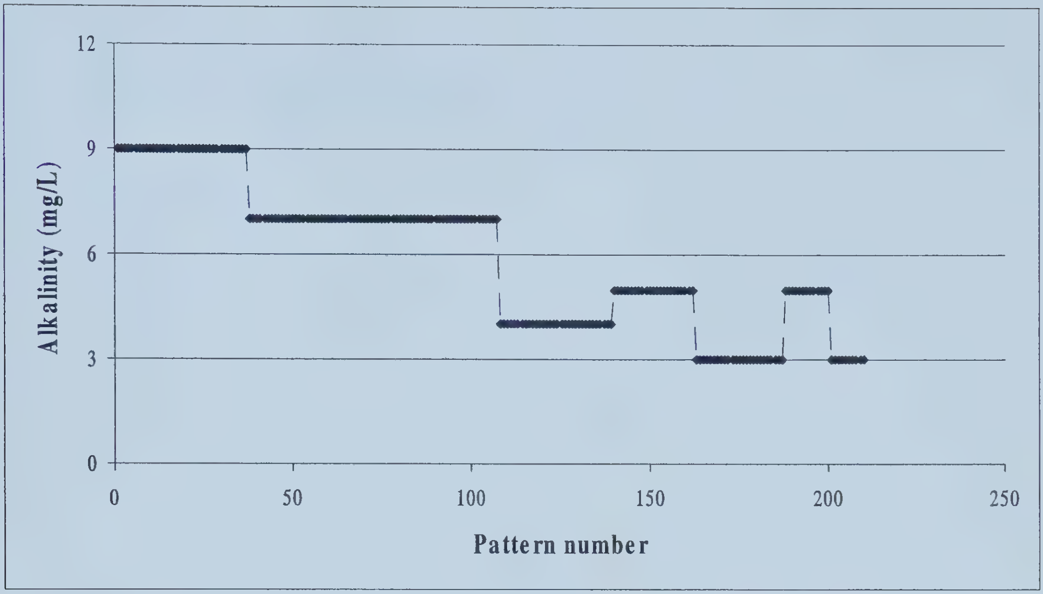

Figure 4-37 DAF bench-scale study, raw water alkalinity.

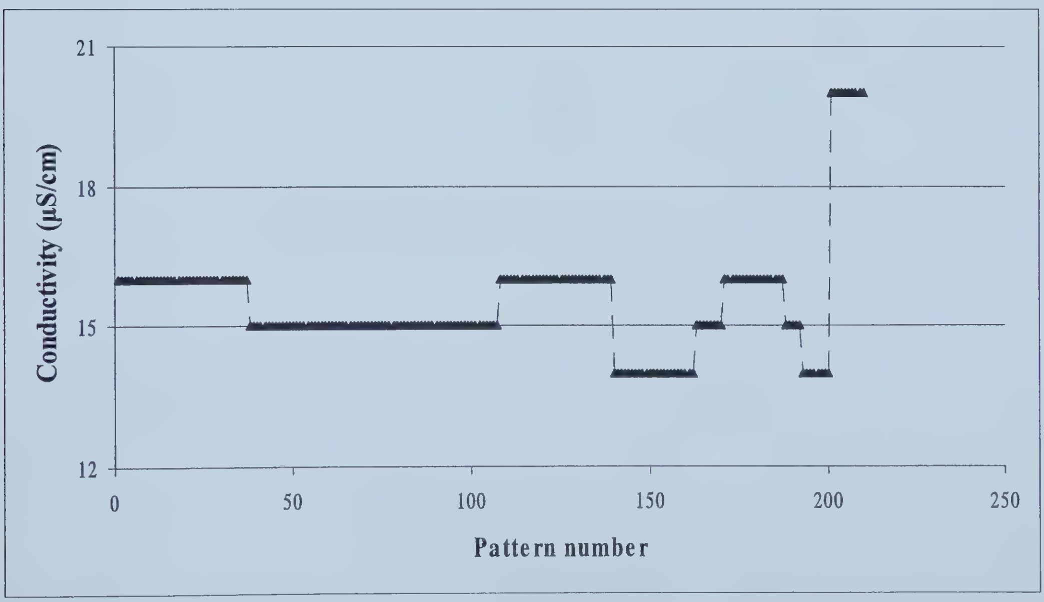

Figure 4-38 DAF bench-scale study, raw water conductivity.

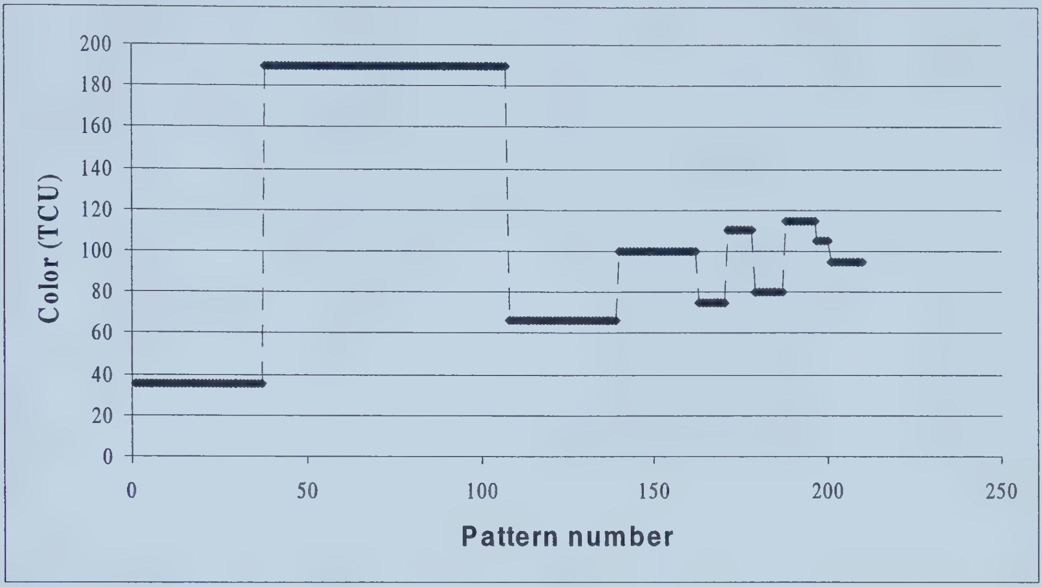

Figure 4-39 DAF bench-scale study, raw water color.

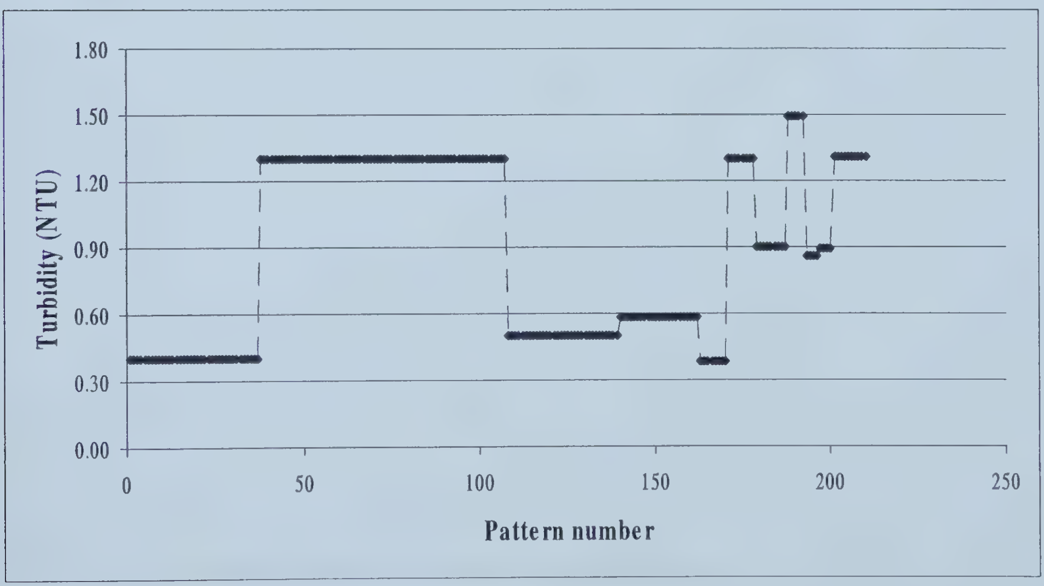

Figure 4-40 DAF bench-scale study, raw water turbidity.

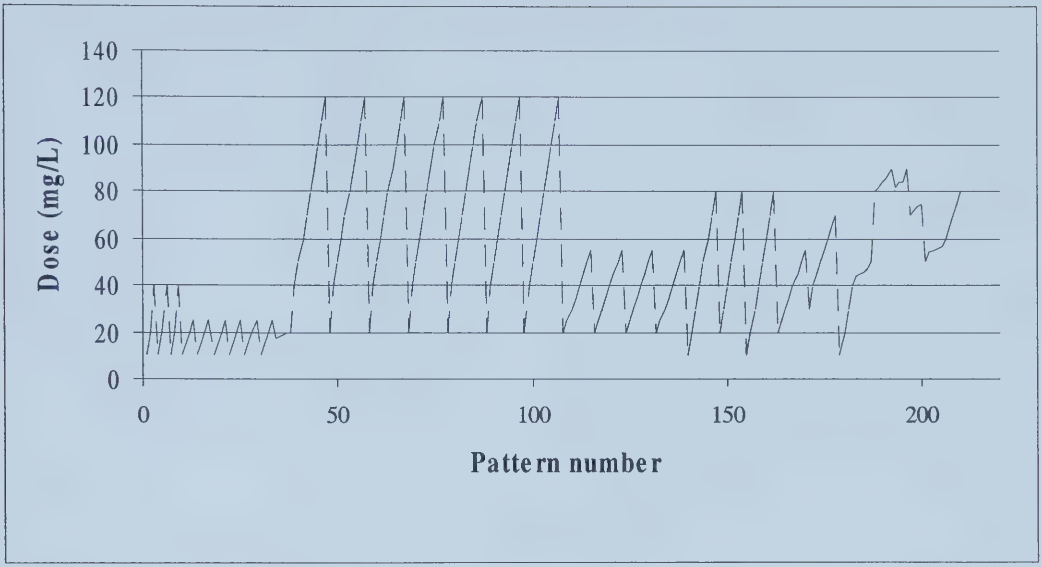

Figure 4-41 DAF bench-scale study, alum dose.

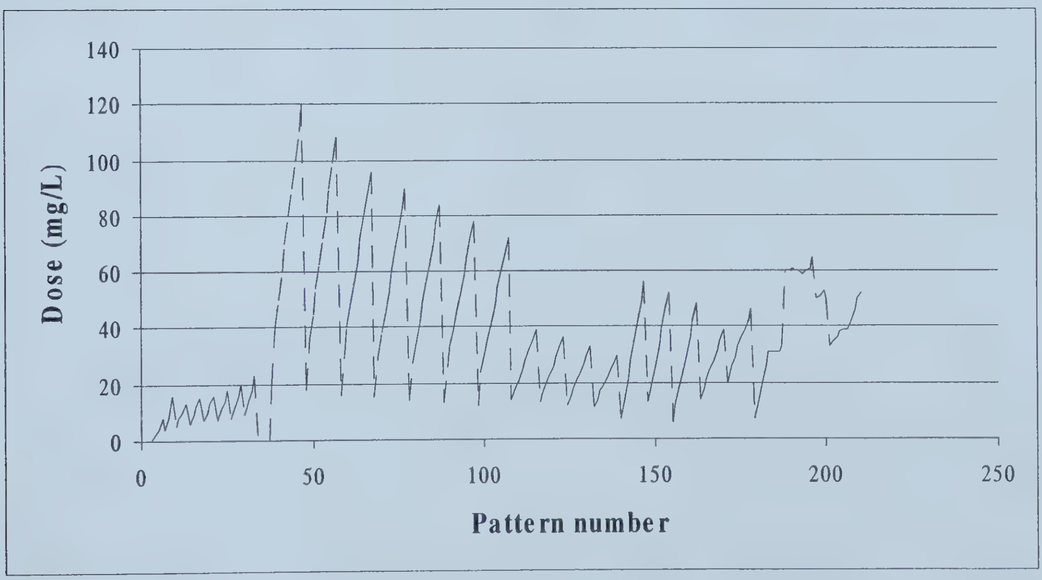

Figure 4-42 DAF bench-scale study, soda ash dose.

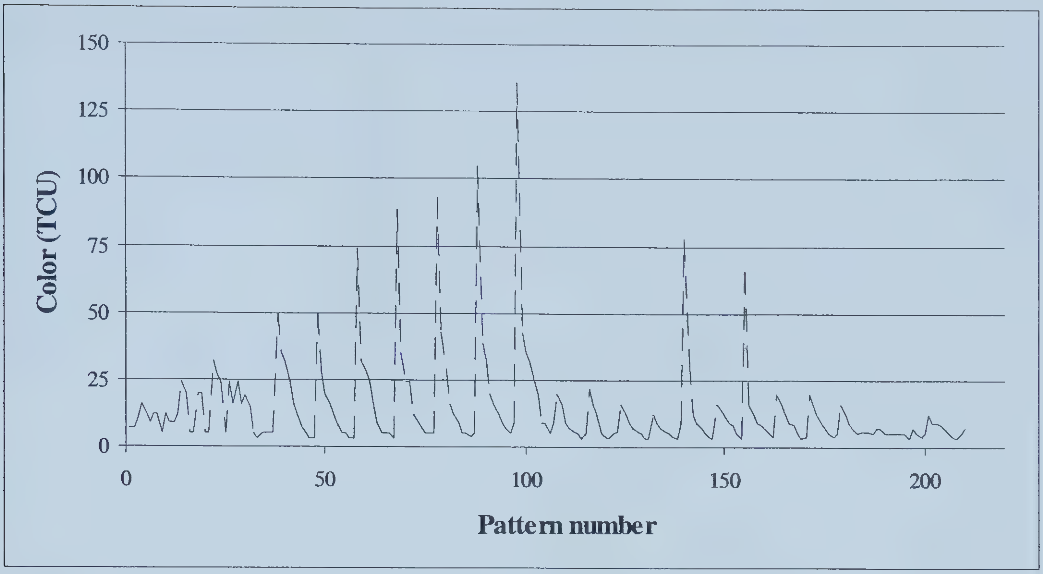

Figure 4-43 DAF bench-scale study, effluent color.

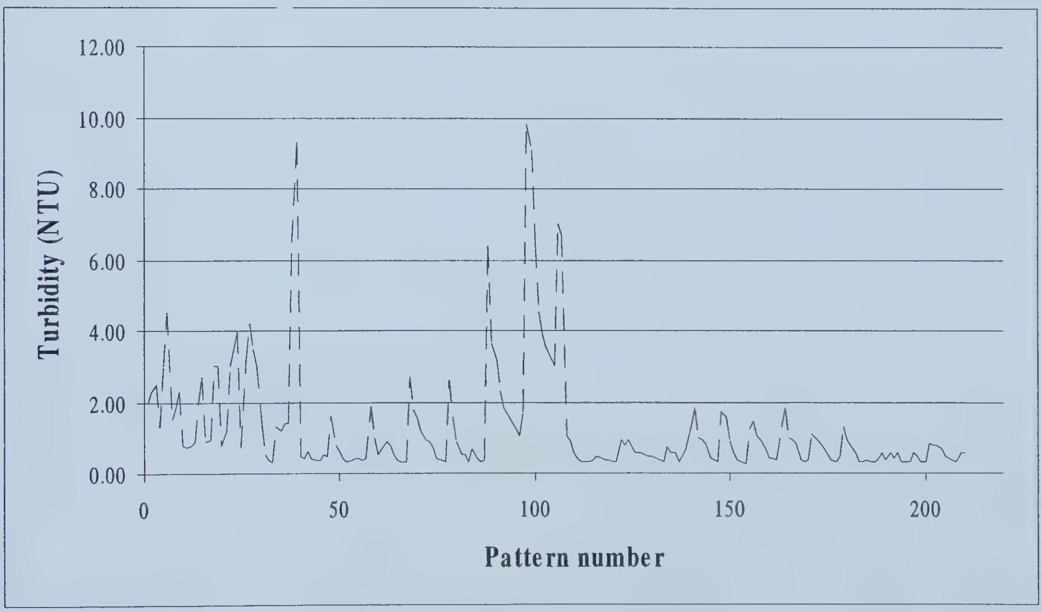

Figure 4-44 DAF bench scale study, effluent turbidity.

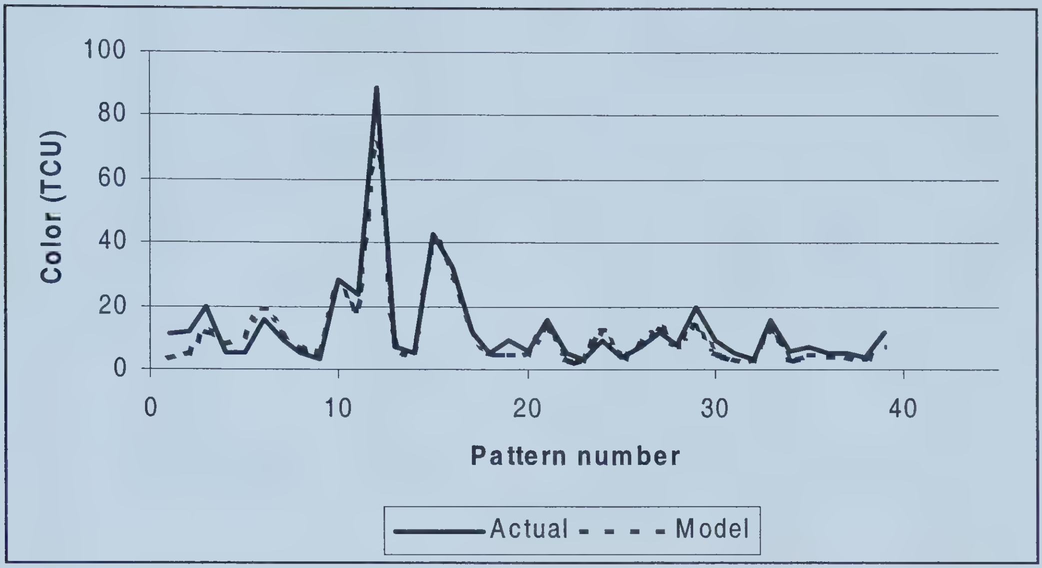

Figure 4-45 Color model results for production data pattern in bench-scale DAF.

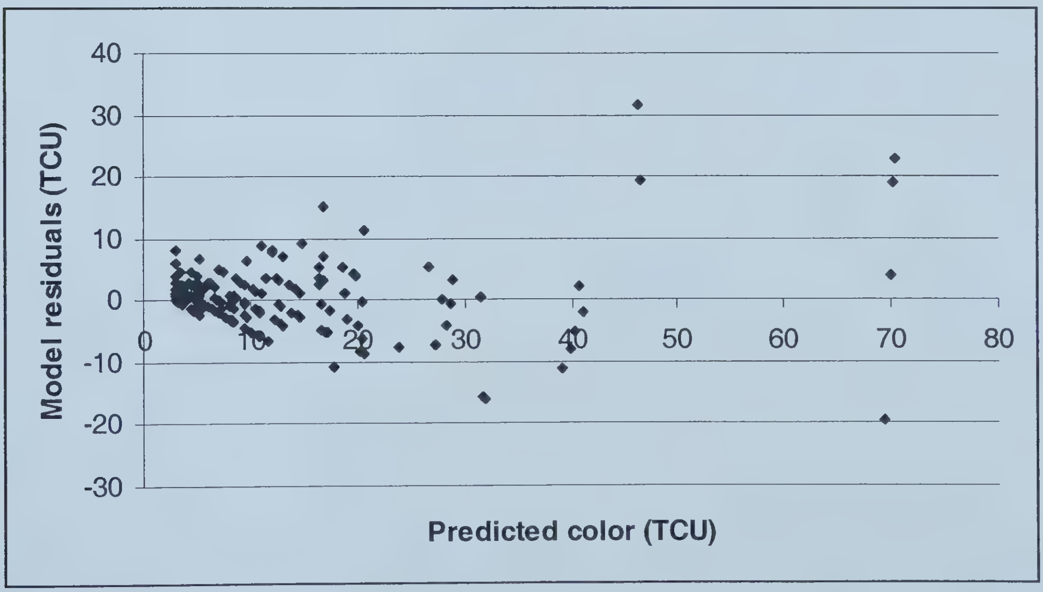

Figure 4-46 Color model residuals in bench-scale DAF.

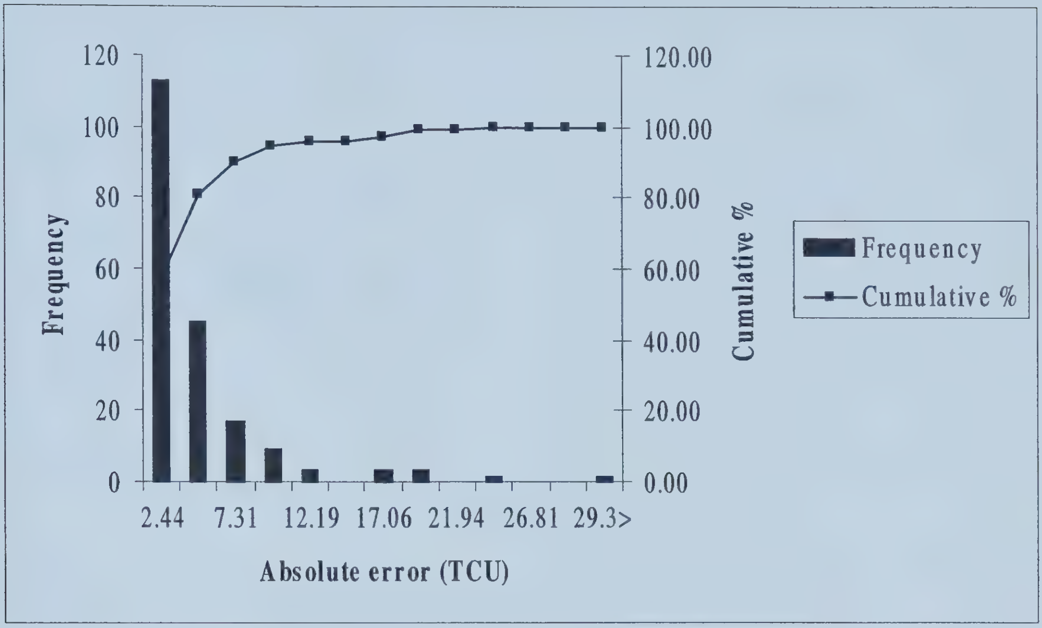

Figure 4-47 Distribution of absolute error for the bench-scale DAF color model.

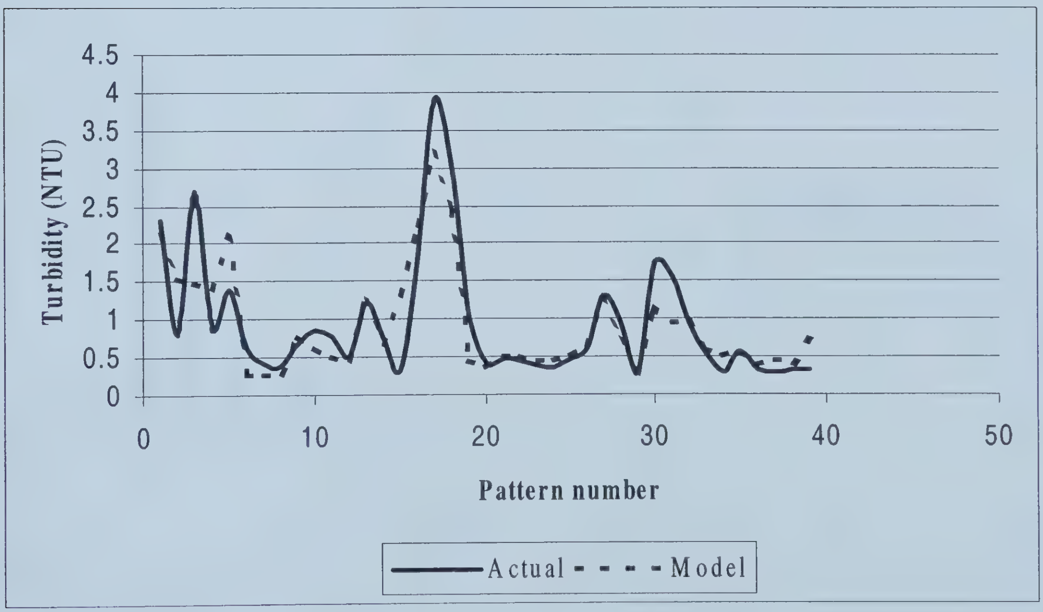

Figure 4-48 Turbidity model results for production data sets in bench-scale DAF.

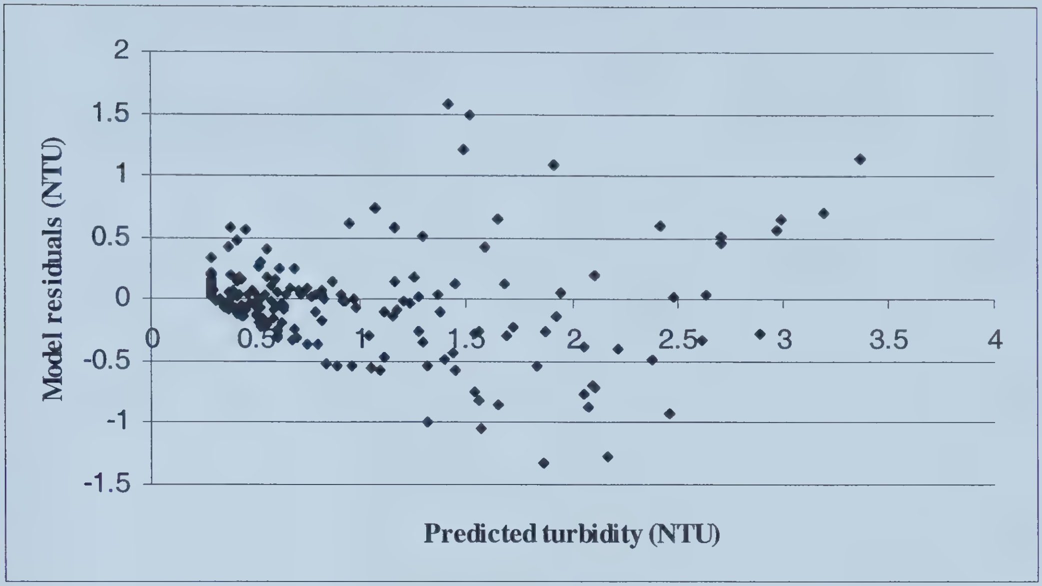

Figure 4-49 Turbidity model residuals in bench-scale DAF.

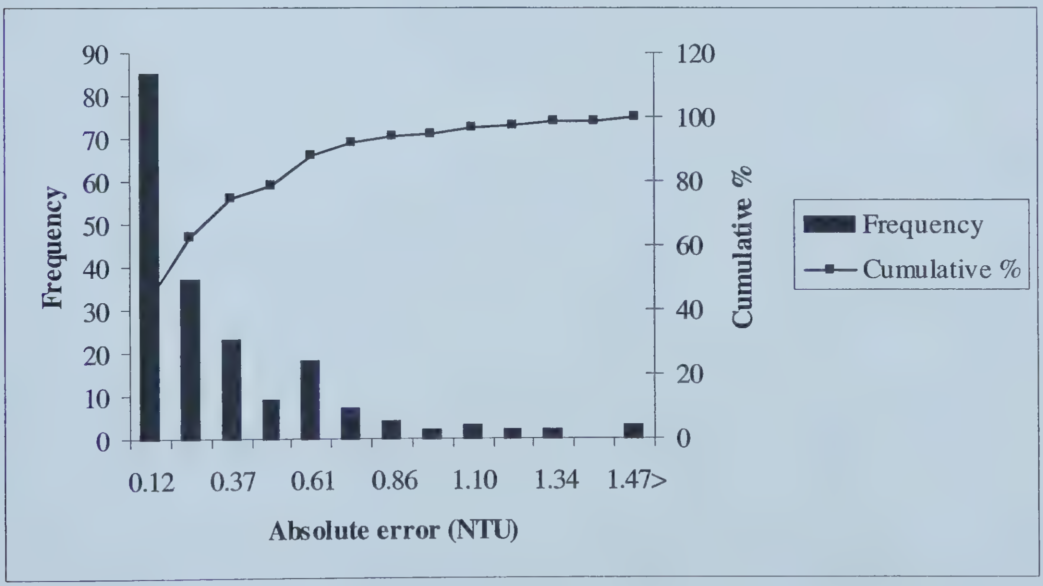

Figure 4-50 Distribution of absolute error for the bench-scale DAF turbidity model.

5 DISCUSSION

5.1 DAF Full-Scale Evaluation

The best model was selected on the basis of the lowest mean absolute error from a number of potential candidate model architectures. When the trained networks were applied to each of the data sets for the color model, the results from Table 4-6, were consistent and ranged from R^2 value of 0.58 for the testing set to 0.66 for the production set. The R^2 value for the training data set was 0.60. Similarly the mean absolute error ranged from 1.2 TCU in the production set to 1.3 TCU in the testing set. The mean absolute error for the training data set was 1.2 TCU. When the testing and production data patterns were swapped and the model was retrained, the new production data patterns yielded a R^2 value of 0.61 with a mean absolute error of 1.3 TCU, which was nearly identical to the original test set. This indicated that the model was stable.

When the trained network was applied to the training, testing and production data set in the turbidity model, from Table 4-7, the R^2 value ranges from 0.63 in the testing data set to 0.67 in the training data set. The mean absolute error was 0.03 NTU in the training data set and 0.03 NTU in the testing data set. The R^2 value for the production data set was 0.64 and the mean absolute error was 0.03 NTU. When the testing and production data patterns were swapped and the model was retrained, the new production data patterns yield R^2 value of 0.63 with a mean absolute error of 0.03 NTU, which was identical to the original test set. This also indicated that the model was stable.

The full-scale color model results for the previously unseen data (production data patterns) are presented graphically in Figure 4-13. The model had good trends with most of the errors attributable to instrumental variability. The model followed the trends quite well but not to the best due the instrumental deficiency in measuring DAF effluent color. In the first twenty patterns when the DAF effluent color ranged from 0.50 TCU to 1 TCU, the network model tended to over predict the actual values. This error was further verified with the pilot plant data and more on experience of the full-scale plant, which suggested that the DAF effluent color was rarely below 1 TCU with the same kind of raw water quality and plant operation. This error was mainly due to the instrumental deficiency. The model had few deficiencies in predicting the highest peak of the DAF color effluent. The model could predict that there was a peak, however, it tended to under predict the actual effluent color by 1 TCU to 1.8 TCU. The highest peak was observed during the month of July 2002 when the raw water color was 40 TCU. The alum dose applied was 26 mg/L. This under dosing of alum led to mild upset in the plant.

The unsupervised training of the Kohonen self organizing feature map was used successfully as means of advanced sorting method to categorize the data according to the seasonal variation and operational conditions. The Kohonen self-organizing feature map was used to separate data into a user-specified number of clusters or categories. The KNN consisted of only two layers, an input layer with one node for each input variable in the category, and the output layer with one node. The Kohonen SOFMs was presented in greater detail by Kohonen (1982). The goal of the KNN algorithm was to map a multidimensional input into a two dimensional output nodes. The training patterns were

presented to the input layer and then propagated to the output layer for evaluation. The output neuron that classified the feature in the input pattern more accurately was the winner. The size of the neighbourhood is usually starts off to be one less than the number of categories. However, this technique was deployed in building the color model and was useful as there was instrumental deficiency existing in measuring the DAF effluent color. The technique was quite good over traditional approach of sorting the data according to the effluent parameter.

The turbidity model results for the previously unseen data (production data) are presented graphically in Figure 4-16. The full-scale turbidity model could follow the trends quite well, but had some difficulties in recognizing the highest turbidity peak accurately. This needs further examination. The network tended to over-predict the actual values in the first 20 data patterns when the actual DAF effluent turbidity ranges from 0.26 NTU to 0.30 NTU. However, the error was very nominal (0.05 NTU) and can be regarded as negligible. Although the model had some difficulty in predicting the highest DAF effluent turbidity peaks, the model could recognize that there was a peak quite well. It tended to under-predict the peaks. In the pattern numbers 21, 38 and 46 when the clarifier actual turbidity ranged from 0.34 NTU to 0.44 NTU, the network tended to under predict by approximately 0.10 NTU. The largest prediction error in the whole data pattern was found when the DAF effluent turbidity was 0.44 NTU and 0.34 NTU in the production data set and the model prediction was 0.34 NTU and 0.24 NTU. The actual turbidity peak of 0.44 NTU was the result of mild upset in the DAF clarification process and does not represent the normal operating condition. As such, it was not absolutely

necessary to predict these peaks with complete accuracy. The 90% of DAF effluent turbidity at Port Hardy Water Treatment Plant was within the normal operating range between 0.30 NTU and 0.35 NTU. In this normal operating range, the accuracy increased with an absolute error of only 0.02 NTU in the production set.

Sensitivity analysis performed on each of the parameters for both the color model and the turbidity model indicated that the most important factors influencing DAF effluent color and DAF effluent turbidity during the DAF operation were raw water pH, color, turbidity and alum dose. However, while building the model, all the input parameters that might influence the performance of the model output were considered and those found to be less important were removed in subsequent trials to ensure that the best model was obtained. According to the color model, the most important factors in removing color from DAF in descending order are temperature, pH, color, flow rate and alum dose. The most important factors in removing turbidity from DAF in descending order are temperature, turbidity, pH, alum, flow rate, conductivity, and alkalinity. There were strong correlations between alum dose and soda ash dose, and between raw water color and raw water turbidity. In the turbidity model building process, raw water color did not appear as an important cause-effect parameter. The model considered raw water turbidity as a more important parameter, and the raw water color was left redundant during the model building process. Both models found soda ash less important during the model building process. The models were less sensitive to alum possibly because alum was spread over too narrow a range for noticeable effect to be observed. However, the range examined for alum dose is between 21 mg/L and 122 mg/L. There was a strong

correlation between influent color, alum and turbidity. The model might have recognized one of them as very important, and the other less important.

In order to ensure that there was no obvious trend in the model residuals, the plot of the model residuals against predicted DAF effluent color in production data set presented in Figure 4-13 suggested that the majority of the color model residuals fall within a narrow band in the range of –1.0 TCU to 1.0 TCU. The distribution of the model absolute error also showed that mean absolute error was below 1.5 TCU in almost 80% of the data patterns in production set. The plot of the model residual against the predicted DAF effluent color in production data set presented in Figure 4-17 suggested that the majority of the turbidity model residuals fall within a narrow band in the range of 0.025 NTU to –0.025 NTU. The distribution of the model absolute error also showed that mean absolute error was below 0.025 NTU in almost 85% of the data patterns in production set. However, the over dosing of the chemicals have an important impact on DAF effluent. When overdosing occurred, the flocs get heavier and remain at the bottom of the clarifier and do not come out instantly with the effluent turbidity. However, over dosing of chemicals were reflected at the DAF effluent color. As such, DAF color model is more accurate to determine the DAF performance. The accuracy of the model can be fixed with operational experience, fine-tuning the model in course of time when the model is online, or from the pilot plant data.

5.2 DAF Pilot-Scale Evaluation

The best model was chosen with the least mean absolute error from a number of potential candidate model architectures. When the trained networks were applied to each of the data sets for the color model, the results in Table 4-12 were consistent and were ranging from R^2 value of 0.79 to 0.84. Similarly the mean absolute error ranged from 0.9 TCU to 1.2 TCU. The R^2 value of the production data set was 0.84 with a mean absolute error of 1.2 TCU. For the turbidity model, from Table 4-13, when the trained network was applied to the training, testing and production data set, the R^2 value ranged from 0.35 to 0.47 and the mean absolute error ranged from 0.07 NTU to 0.09 NTU. The R^2 value for the production data set was 0.47 and the mean absolute error was 0.09 NTU. Even though, R^2 value of the turbidity model was not as good as the color model from pilot study data, however, the model could predict most of the peaks. The R^2 value as well as absolute mean square error of the model could be improved by feeding more data points to the model training data set, which is possible by conducting further research. Increasing training data patterns of the similar range could minimize the prediction error in such cases (Baxter et al. 2002a). However, all the data patterns collected during the study were deployed building ANN models and increasing the data patterns in training set is only possible by collecting further data patterns.

The color model provided excellent predictions in most of the data points with small absolute prediction error. The color model results are presented graphically in Figure 4-29. The model could follow all the trends quite well. In the first few patterns when the DAF effluent color is between 5 TCU and 8 TCU, the network tends to over

predict the actual values by approximately 2 TCU. However, this happened during the normal operating condition and the small magnitude of 2 TCU is negligible from the process control standpoint prior to filtration. The model had some difficulties in predicting the highest DAF effluent color peaks. The model clearly recognized that there is a certain peak but it had a tendency to under predict the actual DAF effluent color in the production data set. Since the effluent color peaks are the results of mild upsets in the DAF clarification process, and they do not fall on the regular operating condition, however it is not absolutely necessary to predict these peaks accurately. The model had good predictive capacity at normal operating range (depends on raw water color). The largest prediction error in the whole data patterns was found when the value of DAF effluent color was 22 TCU, much higher than the average effluent color obtained during the study and the model prediction for that particular data pattern was 18.1 TCU. However, this largest mean absolute error was in production set. This could be due to the lack of similar data patterns in the training data set. There was only one data pattern in the training set containing higher effluent color of 20 TCU and four data patterns exceeding 10 TCU. The model also over predicted the DAF effluent color with a magnitude of 2.9 TCU in the production data patterns. This was the case when alum-soda ash ratio was lower than the required and the plant might have experienced mild upset situation in the clarifier, which is very rare in regular full-scale operation. These data were generated to investigate the effect of lesser ratio of alum and soda ash than the optimal and this further demonstrated the importance of keeping alum and soda ash ratio in the optimal range. However, the model was built with a limited number of data

patterns and as such the model may not have enough data to generate accurate predictions in this range.

The turbidity model also provided excellent predictions capabilities with mean absolute prediction error of 0.09 NTU. The model results are presented graphically in Figure 4-32. The model follows the trends in predicting DAF effluent turbidity quite well except it had few difficulties in predicting the peaks more accurately. The network tends to over predict the DAF effluent turbidity in few cases when the turbidity value ranges from 0.60 NTU to 0.70 NTU. The major over prediction occurred at run number 70 when the model predicted the DAF effluent turbidity as 0.90 NTU and the actual value was 0.63 NTU. This happened when the pilot plant was operating with lower dose of alum (20 mg/L) and soda ash dose of (13 mg/L) at raw water color of 66 TCU, which is rare in process control point of view in the full-scale treatment. This over prediction could be due to the lack of data in the training set at this operating range. The model clearly recognized that there is a peak, however, it tends to under predict the actual DAF effluent turbidity by approximately 0.40 NTU. Both the peaks in the data patterns are the result of mild upsets in the DAF clarifier, and they do not fall in the range of regular operating conditions. However, the model under estimated few peaks when the DAF effluent turbidity was 1.26 NTU and 1.28 NTU and the model prediction was 0.80 NTU and 0.89 NTU respectively. The DAF effluent turbidity from the pilot plant was always higher than the full-scale DAF effluent and it never reached below 0.50 NTU while with the same dose and operating condition the full-scale DAF generated lower turbidity than 0.35 NTU. The higher effluent turbidity was also found when the alum dose or soda ash dose

were not at their best optimum range (higher or lower dosages occurred) or the pH in the DAF clarifier was not between 6.3 and 6.8. The largest prediction error in the whole data patterns was found when the value of DAF effluent turbidity was 1.48 NTU, the maximum effluent turbidity obtained during the operation of the DAF pilot plant. However, this largest mean absolute error was in production data set. This is also due to the lack of similar data patterns in the training data set. The turbidity model could miss a few peaks, as there is limited number of data patterns higher than 1 NTU. The pilot plant was designed for algae removal and gave very good performance with higher hydraulic loading rate at 70 m/hr (Shawwa and Smith 1998). However, the pilot plant at Port Hardy was operated at lower hydraulic loading rate and gave good result at 15 m^3/m^2-hr hydraulic loading rate for color removal. Moreover, the saturation system of the pilot plant was a batch process. Two of the saturation tanks could provide 30 minutes operation without disturbance and the tank had to be filled with water every 30 minutes. It was very difficult to maintain the same bubble rising velocity and fine bubble size once the saturation tank was refilled and replaced with the new one. The clarifier size of the pilot plant was small and there was no delineation boundary between the contact zone column and the clarifier zone. As a result, there was a good chance of short-circuiting during the operation and fine bubbles also contributed to the DAF effluent turbidity. Thus, the long operation time of the pilot plant (4 detention time or 2 hrs) at lower hydraulic loading rate, and the small size of the clarifier, the batch nature of the saturation system might have negative impact on the DAF effluent turbidity. For the pilot plant operation, DAF effluent turbidity higher than 1 NTU represented as plant upset.

Sensitivity analysis performed on each of the parameters for both the color model and turbidity model indicated that the most important factors influencing DAF effluent color and DAF effluent turbidity during the pilot run were alum dose, raw color, soda ash dose. The dosing rate at Port Hardy Water Treatment Plant was determined based on color of the raw water. The sensitivity analyses performed on models support the fact that successful removal of color and turbidity can be achieved with the use of proper coagulant and chemical dosing. The raw water of Port Hardy is low in turbidity and low in alkalinity as stated earlier. The soda ash acted as a buffer to maintain the pH in the clarifier within the optimum range and the successful operation of color removal is highly pH dependent. Nevertheless, sensitivity analyses performed on raw water parameters also suggest that alkalinity, conductivity, temperature and pH had less influence on plant performance. However, according to the color model, the most important factors in removing color from pilot DAF in descending order are alum dose, color, soda ash dose, conductivity, flow rate, turbidity, alkalinity, temperature and pH. The best turbidity model was obtained by eliminating raw water pH and temperature from the model inputs. According to the turbidity model, the most important factors in removing turbidity from DAF pilot unit in descending order are color, soda ash, alum dose, turbidity, flow rate, alkalinity, and conductivity. However, temperature and pH of the raw water did not appear to be one of the important parameters in turbidity model building process, even though they should have. This could be due to the small data sets, and it would have been possible to conclude that the levels evaluated for the given factors were spread over too narrow a range for a noticeable effect to be observed. However, one should keep in mind

that the sensitivity analysis does not indicate the exact effect on the plant performance, however, does indicate the need to take considerations in building the model.

In order to ensure that there are no obvious trends in the model residuals, the plot of the residuals against the data patterns in Figure 4-30 suggested that the majority of the color model residuals fall within a narrow band in the range of –1.0 TCU to 1.0 TCU. The DAF effluent color was measured using an instrument, which is accurate to within 1 TCU. The plot of the residuals against the data patterns in Figure 4-33 suggested that the majority of the turbidity model residuals fall within a narrow band in the range of 0.10 NTU to –0.10 NTU. Building turbidity model from DAF operation was always challenging due to the presence of fine bubbles in the effluent, which might have introduced a significant amount of errors in the turbidity measurement (Hedberg et al. 1998).

5.3 DAF Bench-Scale Evaluation

The best model was chosen with the least mean absolute error from a number of potential candidate model architectures with different hidden layer neurons. When the trained networks were applied to each of the data sets for the color model, the results in Table 4-18 were consistent and were ranging from R^2 value of 0.81 to 0.91. Similarly the mean absolute error ranges from 3.0 TCU to 3.5 TCU. The R^2 value of the production data set for color model was 0.91 with a mean absolute error of 3.0 TCU. However, for

the turbidity model, from Table 4-19, when the trained network was applied to the training, testing and production data set, the R^2 value ranges from 0.72 to 0.75 and the mean absolute error ranges from 0.26 NTU to 0.28 NTU. The R^2 value for the production data set was 0.75 and the mean absolute error was 0.28 NTU. However, the R^2 value as well as absolute mean square error of the model could be improved by feeding more data points to the model training data patterns.

The color model results for the previously unseen data (production data) are presented graphically in Figure 4-45. The model followed the trends of the DAF effluent color quite well and recognizes most of the peaks successfully. The model provided excellent predictions in most of the data points with mean absolute error of 2.99 TCU in the production data set. The largest prediction error in the production data patterns was found when the value of DAF effluent color was 89 TCU and the model predicted 70 TCU. The largest mean absolute error in the whole data patterns was found 31.7 TCU when the value of DAF effluent color was 78 TCU and the model predicted 46.3 TCU. This data pattern was in training set and large mean absolute error could be due to the lack of similar data pattern in the training data set. There were only three data patterns in the training set containing higher effluent color than 65 TCU. From Figure 4-45, the model had some difficulties in predicting the highest clarifier effluent peaks accurately. The major prediction error in the production data set was observed when the DAF effluent color was higher than 85 TCU. While the model clearly recognized that there is a peak, it had a tendency to underestimate the effluent color in greater magnitude. The actual effluent color peaks are the result of mild upsets in the DAF treatment process and

they do not fall within the regular operational conditions. However it is more important that the model has good predictive capacity in the normal operating range (<10 TCU) of DAF effluent color. In this range, the model accuracy is much higher and the mean absolute error is only 1.3 TCU on the production data set.

The turbidity model results for the previously unseen data (production data) are presented graphically in Figure 4-48. The bench-scale turbidity model also predicted well and could recognize all the major peaks with a mean absolute prediction error of 0.28 NTU when the model was applied to the production data set. The model missed only one peak in the production data set when the DAF effluent turbidity was 2.70 NTU and the model prediction was 1.49 NTU. The largest prediction error in the whole data patterns was found when the DAF effluent turbidity was 3 NTU. However, this could be due to the lack of similar data pattern in the training data set. From Figure 4-48, the major prediction error was observed when the DAF effluent turbidity was higher than 1 NTU, which were the results of mild upsets of the system. The turbidity model clearly recognized the peak, however in the first 10 patterns, when the DAF effluent turbidity was 0.8 NTU to 1.5 NTU, the network tends to over predict the actual values. This prediction error was mainly generated from the data patterns that were collected at room temperature. After that, the model was quite well at recognizing the trends, however, the model had difficulty in predicting the DAF effluent turbidity accurately. Moreover, the model was underestimating the peak. The model had good predictive capacity in the normal operating range (<0.50 NTU) of the DAF effluent and the model accuracy increased with an absolute error of 0.05 NTU on the production set. However, the bench-

scale went through the extreme stress test during the operations and showed excellent performance in predicting DAF effluent color and DAF effluent turbidity with high degree of accuracy in the normal operating range.

Sensitivity analysis performed on each of the parameters for both the color model and the turbidity model indicated that the most important factors influencing DAF effluent color and DAF effluent turbidity in bench-scale operation were alum dose, color, temperature and soda ash. The sensitivity analyses support the fact that successful removal of color and turbidity can be achieved with proper coagulation and chemical dosing. Temperature came out as one of the key factors in color removal and turbidity removal. According to the color model, the most important factors in removing color from bench-scale DAF are color, alum dose, conductivity, soda ash dose, alkalinity, temperature, pH, and turbidity. These are in descending order according to their importance in building the model. According to the turbidity model, the most important factors in removing turbidity from DAF pilot unit in descending order according to the importance are soda ash dose, alum dose, color, temperature, turbidity, alkalinity, pH, and conductivity. Again, the sensitivity analysis does not enlighten the exact effect on the plant performance, does indicate the need to take considerations in building the model.

In order to ensure that there are no obvious trends in the model residuals, the plot of the residuals against the predicted data patterns in Figure 4-46 suggested that the majority of the color model residuals fall within a band in the range of –3.0 TCU to 3.0 TCU. The distribution of the absolute prediction error in color model showed that mean

absolute error was below 2.5 TCU in almost 80% of the data patterns in production set. The turbidity residuals plot in Figure 4-49 shows that the majority of the turbidity model residuals fall within a narrow band in the range of 0.28 NTU to -0.28 NTU. The distribution of the model absolute error in Figure 4-50 also showed that mean absolute error was below 0.10 NTU in almost 60% of the data patterns in production set. However, high degree of error was associated from extreme chemical dosing (too high or too low) case when the bench-scale DAF plant experienced severe upset condition. The full-scale operation and the pilot-scale operation did not go through the extreme condition as the bench-scale did. The bench-scale DAF worked well in different raw water conditions while emulating the real treatment plant. As such, the model developed from a series of tests may be useful in process control applications.

The ANN modelling technique appears to hold promise for successful modelling of the DAF treatment processes in bench-scale study. However, the jar tests contain considerable human error in relation to timing and addition of chemicals, which are magnified, as the jar test is such a small scale compared to a full-scale treatment plant.

6 CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

ANN modeling techniques were applied to evaluate the performance of the full-scale DAF at Port Hardy Water Treatment Plant, pilot-scale DAF, and bench-scale DAF treating low turbidity, low alkalinity and color water at Port Hardy, BC. The developed ANN models were able to predict DAF effluent color and DAF effluent turbidity with high degree of accuracy and holds promise for successful ANN control. However, the major findings of this research are as follow:

(1) With respect to performance on historical data, the full-scale color model provided excellent prediction capacity with R^2 value of 0.66 and mean absolute error of 1.15 TCU in the production data set. The model had good trends with most of the errors attributable to instrumental variability. An advanced sorting method using Kohonen SOFMs were used to categorize the data patterns into training, testing and production data set, and was useful in building ANN model successfully. The technique was quite good over traditional approach of sorting due to the existing instrumental deficiency in measuring DAF effluent color. The turbidity model provides excellent prediction capabilities with a R^2 value of 0.64 and mean absolute prediction error of 0.03 NTU in the production data set. It was found that the raw water pH, the raw water temperature, the raw water color, the raw water flow rate and alum dose are the key cause-effect parameters for the color reduction in DAF process.

It was also found that the raw water temperature, raw water turbidity, raw water pH, alum dose, and the raw water flow rate are the key cause-effect parameters for good turbidity control in DAF effluent. The performance of the model is obviously dependent on quality data and completeness of data provided for system training. However, continuous updating of training data during operational use can improve the performance of the models.

(2) With respect to the performance on pilot-scale data, model built from pilot scale data showed excellent capacity in predicting DAF effluent color with a high degree of accuracy. The color model provided a R^2 value of 0.84 with a mean absolute error of 1.2 TCU in the production data set. The turbidity model provided a R^2 value of 0.47 and a mean absolute error of 0.09 NTU when applied to the production data set. The evaluation suggests that ANN color model built from DAF pilot-scale can eventually be used for process evaluation to reduce the frequency and severity of plant upsets. The pilot study conducted at Port Hardy suggested that DAF operation using alum and soda ash was extremely pH sensitive and it worked well within the range of pH between 6.3 and 6.8 in DAF clarifier. However, according to the color model, it was found that alum dose, raw water color, soda ash dose and the raw water flow rate are the key cause-effect parameters for the color reduction in the DAF process. It was also found that during high raw water color, good treatment could be achieved with proper alum dose and soda ash dose. According to the turbidity model, it was found that raw water color, alum dose, soda ash dose and raw water turbidity are the key cause-effect parameters for maintaining DAF effluent turbidity within desired range.

It was also found that good control of turbidity in the DAF effluent, and reasonable treatment can be achieved during the high raw water color scenario with proper alum dose and soda ash dose, and even at lower flow rate.

(3) With respect to the performance on bench-scale data, the bench-scale color model provided excellent prediction capacity with a R^2 value of 0.91 and a mean absolute prediction error of 3.0 TCU in the production data set. The turbidity model provided a R^2 value of 0.75 and a mean absolute error of 0.28 NTU when the model was applied to the production data set. The actual color peaks and turbidity peaks were the results of plant upset in the DAF clarification process and they do not fall within the normal operating range. Since the goal of the process model is to avoid such upsets, it is more important that the model has good predictive capacity in the normal operating range. However, the color model had good predictive capacity in the normal operating range of DAF effluent color (<10 TCU). In this range, the model accuracy was much higher and the mean absolute error was only 1.3 TCU on the production data set. The turbidity model had good predictive capacity in the normal operating range (<0.50 NTU) of the DAF effluent and the model accuracy increased with an absolute error of 0.05 NTU on the production set. The ANN modeling technique appears to hold promise for successful modeling of the DAF treatment processes in bench-scale study. According to the color model, it was found that, the raw water color, alum dose, soda ash dose, temperature are the key cause-effect parameters for the color reduction in bench-scale DAF process. According to the turbidity model, it was found that the raw water color, raw water temperature, soda ash dose, alum dose

are the key cause-effect parameters for better turbidity control in the DAF process. It was also found that warm raw water temperature favours the color reduction and good turbidity control in the DAF process.

(4) The bench-scale study was conducted using raw water color ranges from 30 TCU to 190 TCU. The experiment was also conducted using different coagulant doses and soda ash doses to investigate the performance of the batch plant in extreme situations. Bench-scale modeling data patterns consisted of all these different alum doses and soda ash doses with extreme high and extreme low that caused plant upsets. Most of the major errors were generated from plant-upset conditions in bench-scale ANN models. However, it was not possible to conduct the same stress test on pilot-scale operation due to the unavailability of high color water during the study period at Port Hardy, and also due to the time constraint. Similarly, the daily average data patterns from the full-scale operation consisted of normal operating range, and the data with plant-upset conditions was missing with questionable entries. However, in normal operating range the bench-scale could perform excellent and could emulate the full-scale DAF quite successfully producing same quality of treated water. Moreover, there was not enough difference in producing DAF effluent color from the pilot-scale and bench-scale operations. As such, a series of data generated from bench-scale study may be useful for successful process control of the DAF plant in full-scale operation. However, there are many limitations of moving from a jar test to a full-scale operation. These may include, but are not limited to, some of the following:

(i) Full-scale plants experience spikes in their raw water quality, whereas jar tests are an instantaneous test and are not representative of varying conditions.

(ii) The plant operates all year around and is exposed to varying temperature conditions, whereas the jar test provides results merely for the temperature of the test water.

(iii) The jar tests contain considerable human error in relation to timing and addition of chemicals, which are magnified, as the jar test is such a small scale compared to a full-scale treatment plant.

(5) It was also observed from bench-scale DAF operations that the effluent water quality is extremely pH dependent in the DAF clarifier when alum and soda ash is used. The optimum pH range of the DAF clarifier is between 6.3 and 6.8.

(6) The bench-scale study was conducted using different coagulants such as alum as base coagulant, and polyaluminum chloride of different basicity (high, medium and low). The results using high basicity polyaluminum chloride suggested good pH and turbidity control of the DAF treated water and promising practical applications in treating low alkalinity, low turbidity and colored water. However, two critical areas warrant further research. First, these reported studies did not involve post filtration research. Secondly, the studies reported here is batch, bench-scale efforts. The true effectiveness of optimum coagulant dose can be established and further verified with pilot and eventually full-scale confirmation.

6.2 Recommendations

Based on this research, a number of recommendations are made for further study:

1) Inverse ANN model predicting chemical doses may be developed for successful process control in Port Hardy Water Treatment Plant.

2) The performance of the network is dependent on the quality and completeness of training data. Continuous updating of training data during operational use is recommended.

3) ANN cannot reveal the direct mechanistic relationship between the water quality data and required coagulant dosages. Therefore, the training data should be prepared correctly to derive a reliable ANN prediction.

4) Pilot-scale study may be conducted to gather more data in winter storm event during high color situations in the Tsulquate River. This would give a wide range of operation in developing process control model using ANN.

5) The pilot study as well as the bench-scale study supports the fact that the DAF operation is extremely pH sensitive. The DAF effluent color and turbidity can be controlled if the DAF clarifier pH is controlled within the range between 6.3 and

6.8. Therefore, advanced process control technique using ANN modeling technique may be used to predict DAF clarifier pH.

6) The alum and soda ash dose selected should have an important impact on the results and it is imperative that the operator understands these impacts. Literature review and bench-scale study further suggests that high basicity polyaluminum chloride may be used as alternate coagulant for better pH control and excellent finished water quality. However, this needs pilot-scale and eventually full-scale confirmation.

7) If jar testing is to be performed, procedures should be thoroughly documented and tailored to the specific treatment plant. The test is sensitive to subtle changes in addition of chemicals and timing of mixing durations. Therefore, becoming familiar with all the procedures of jar testing is essential before using the test to dictate treatment conditions.

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APPENDIX A
DETAILED ANALYTICAL METHODS

A1. Lab Procedure for Color Measurement

Required apparatus:

-Aspirator, vacuum

-Filter holder, 47 nm, 300 mL graduated

-Membrane filter (0.45 microns pore size with 47 mm diameter)

-Flask, filtering, 500 mL

-Pipette, volumetric, 50 mL

-Stopper

-Color Standard Solution, 500 platinum-cobalt units

-Flask, volumetric, 100 mL

-DI water

-40 mL glass vial

-Glass cuvet

-Spectrophotometer

-Thermometer

Procedure

1. Assemble the filtering apparatus (membrane filter, filter holder, filter flask and aspirator).

2. Rinse the filter by pouring about 50 mL of deionized water through the filter. Discard the rinse water.
3. Use 50mL of sample at a room temperature
4. If sample is very turbid and takes too long to pass through the cellulose filter, filter through a Whatman glass microfibre filter.
5. Filter through 0.45 microns pore size membrane filter (Fisher Cat. No. 09-719-2E) using a Gelman membrane filter holder. Collect filtrate in a 40 mL glass vial. 40 mL glass vials work well.
6. Prepare calibration curve. Use platinum Cobalt Color standard solution (Fisher Cat. No. SP120-500). Undiluted is equivalent to 500 color units (CU). Prepare 50, 100, 200, 300, 400 CU standards. Store standards at 4°C. Agitate and warm them to room temperature. Do not agitate again to prevent suspending particles.
7. Measure absorbance at 455 nm using glass cuvet. Spec should be warmed up for 30 minutes before using. Blank reference = DI water.
8. Get true color unit (TCU) from the standard curve (absorbance at 455 nm vs. Pt.-Co color unit).
9. If sample > 500 CU, dilute.

APPENDIX B
BENCH-SCALE EVALUATION WITH VARIOUS COAGULANTS

B.1 Introduction and Scope

The Port Hardy Water Treatment Plant draws its raw water from the Tsulquate River. The main treatment issues surround organic color, low turbidity, and lack of alkalinity. Dissolved air flotation (DAF) is the best available technology (BAT) in treating low turbidity, low alkalinity and color water. At present, alum is used as coagulant. The problem arises when the raw water color goes beyond 100 TCU and require high alum dose (dose closer to the true color loading), result in coagulant cost, and sludge removal costs. The Port Hardy water was evaluated with different coagulants. Raw water was shipped from Port Hardy, British Columbia to the University of Alberta. The container used for the shipment was of 1.2 m^3 of volume. This raw water was used for bench-scale evaluation using various coagulants.

B.2 Coagulants and Experimental Design

The coagulants included: 1) alum as reference coagulant; 2) ISOPAC80, a high basicity polyaluminum chloride with 80% basicity; 3) STERNPAC70, high basicity sulfate based polyaluminum chloride with 70% basicity; 4) PASS-C, a medium basicity polyaluminum chloride with 50% basicity. Polyaluminum chlorides (PACs) were supplied by Easy Treat Environmental, Calgary, Alberta (ISOPAC80), Sternpac, Brantford, Ontario (STERNPAC70), and Eagle Brook, Brantford, Ontario (PASS-C). Soda ash was used along with alum for better hydrolysis. However, soda ash was applied only when alum was used as a coagulant. The chemical and coagulants studied are listed in Table B-1.

Table B-1. List of chemical and coagulants

General Name	Product	Al Wt. (%)	Sp. Gravity	Basicity	Other
Aluminum Sulfate	Alum	-	1.345	-	-
Soda Ash	Sodium Carbonate	-	0.96	-	-
High basicity PAC	ISOPAC-80		1.34	80%	-
PAC with sulfate	STERNPAC-70	10.4	1.23	70%	sulfate <2%
Medium basicity PAC	PASS-C	10	1.24	55%	-

The experimental work was performed at the bench-scale using Aztec jar tester. The standard protocol developed for bench-scale study was followed. The standard protocol for bench-scale study is in greater detail in methodology section. The DAF treatment performance was monitored by measuring particle count, true color, turbidity. The raw water quality parameters (temperature, pH, alkalinity, conductivity, UV_{254} absorbance, color, turbidity, particle counts) were also measured in the laboratory. In general, the methods followed Standard Methods (19^{th} edition 1995) or comparable EPCOR standard protocols. The raw water characteristics used during the experiment are summarized in Table B-2.

Table B-2 Characteristics of raw water

Parameter	Units	Port Hardy Water
pH		6.7
Turbidity	NTU	0.40
Color	TCU	35
Particle concentration	number/mL	915
Conductivity	μS/cm	4.0
UV absorbance at 254 nm	cm^{-1}	0.183
Alkalinity	mg/L as $CaCO_3$	9

(September, 2002 shipment from Port Hardy at room temperature 21°C)

B.3 Results and Discussion

The experiment was performed at room temperature in order to determine the optimum coagulant dose. Optimum doses were defined as those that produce low turbidity, highest color removal (<5 TCU) and highest overall particle removal as well as highest particle log reduction while the higher doses produced only marginal improvements. The overall particle concentration greater than the raw water was considered as 0% removal. The performance of different coagulants treating Port Hardy water is summarized in Table B-3 and Table B-4.

Table B-3 Performance of different coagulants treating Port Hardy water

Coagulant Dose (mg/L)				Treated water							
				Color (Pt-Co unit)				Turbidity (NTU)			
*Alum	ISOPAC	STERNPAC	PASS-C	*Alum	ISOPAC	STERNPAC	PASS-C	*Alum	ISOPAC	STERNPAC	PASS-C
0	0	0	0	35	35	35	35	0.4	0.40	0.40	0.40
5	5	15	5	32	35	35	32	0.85	0.25	0.40	0.55
10	10	20	15	12	12	28	28	2	1.20	0.49	0.51
15	12	25	20	9	5	5	28	0.75	0.45	0.65	0.72
20	14	28	25	5	5	5	24	0.4	0.28	0.45	1.10
23	15	30	30	5	5	5	20	0.65	0.20	0.15	1.50
24	16	32	34	5	5	5	5	0.62	0.24	0.20	0.35
25	20	35	35	5	5	5	5	0.62	1.60	0.20	0.22
30	25	40	40	5	16	32	5	0.6	1.80	8.80	0.25
50	30	50	50	12	28	28	5	2.4	2.50	10.00	0.51

Table B-4 Performance of different coagulants treating Port Hardy water

Coagulant Dose (mg/L)				Treated water							
				Overall particle removal(%)				pH			
*Alum	ISOPAC	STERNPAC	PASS-C	*Alum	ISOPAC	STERNPAC	PASS-C	*Alum	ISOPAC	STERNPAC	PASS-C
0	0	0	0	0.00	0	0	0	6.70	6.70	6.70	6.70
5	5	15	5	0.00	40	18	45	6.30	6.70	6.60	6.51
10	10	20	15	0.00	69	39	48	5.82	6.60	6.60	6.40
15	12	25	20	58.00	88	64	46	5.50	6.60	6.30	6.40
20	14	28	25	84.00	97	79	57	5.30	6.60	6.20	6.42
23	15	30	30	88.00	98	80	56	5.20	6.60	6.20	6.28
24	16	32	34	89.00	78	74	90	5.18	6.50	6.10	6.20
25	20	35	35	89.00	0	72	99	5.18	6.40	6.00	6.15
30	25	40	40	80.00	0	54	90	5.00	6.30	5.50	6.00
50	30	50	50	0.00	0	51	60	4.52	6.20	5.00	5.80

The comparison of effluent water quality was based on highest removal from the raw water of turbidity, which is a surrogate measure of suspended particulates, true color, which is a surrogate measure of organic content, and overall particle removal. All the coagulants including alum and PACl were effective in removing color to 5 TCU at their optimum doses. However, alum along with soda ash (ratio of alum-soda ash of 0.90); PASS-C yielded good removal of color (5 TCU) at wider range. An overdosing was observed for PASS-C for color removal of treated water. The summary of color removal using different coagulants is showed in Figure B-1.

For % removal of turbidity STERNPAC-70, PASS-C as well as ISOPAC-80 gave the highest % removal at the optimum dose of 30 mg/L, 35 mg/L and 15 mg/L, respectively. It was found that aluminum based PAC had a better control over treated water turbidity. Alum along with soda ash showed the poorest performance for turbidity control of treated water. Moreover, it was not possible at all to achieve the treated water turbidity below the raw water turbidity using alum with soda ash. At greater or lesser doses than the optimum, alum actually increased the turbidity of the treated water. Alum yielded high turbidity and low pH compared to the other coagulants. The high turbidity support the premise that alum floc particles may not attach to effectively to bubbles at the zero point of charge due to hydrophilic effects. One should note that this effect increases in cold water. Three of the coagulants (sulfate containing STERNPAC-70; high basicity ISOPAC-80 and medium basicity PASS-C) produced as low turbidity as near 0.15 NTU. When alum was used alone, residual turbidity were greater than 1NTU. It was found that alum (25 mg/L) along with soda ash (23 mg/L) improved the performance and reduced

residual turbidity. The summary of turbidity removal using different coagulants is showed in Figure B-2.

For overall particle removal, high basicity ISOPAC-80 and PASS-C gave highest % removal of 98% and 99% at their optimum dose of 15 mg/L and 35 mg/L respectively. On the other hand, STERNPAC-70 and alum with soda ash gave 80% and 89% overall particle removal at the optimum dose of 30 mg/L and 25 mg/L respectively. It was understood from the experiment that, high basicity polyaluminum chloride ISOPAC-80 had the best performance on both turbidity removal and overall particle removal at the lower dose of 15 mg/L. However, medium basicity polyaluminum chloride PASS-C had the equal performance for turbidity and particle removal at higher dose of 35 mg/L. Figure B-3 shows the overall particle % removal of treated water after DAF at different coagulant doses.

The treated water pH at different optimum coagulant doses is presented in Figure B-4. ISOPAC-80 had the slightest effect on raw water pH. The raw water pH of Port Hardy water was 6.7 and the high basicity ISOPAC-80 yielded the finished water pH of 6.6 (at optimum dose), which is very close to the raw water pH. PASS-C and STERNPAC-70 yielded the treated water pH of 6.1 and 6.2 respectively at their optimum dose. Alum along with soda ash yielded the treated water pH of 5.2, which is corrosive in nature. Lower ratio of soda ash to alum yielded better pH control with very high treated water turbidity and particle concentration. However, in treating Port Hardy water (low in

turbidity, low in alkalinity water) high basicity PACl is definitely would be a better choice for the pH control of the treated water.

In general alum with soda ash gave the poorest performance with less control over residual turbidity and pH of Port Hardy treated water. ISOPAC-80 yielded the best result at low dosage and gave good control over residual turbidity and treated water pH. On the other hand, PASS-C showed the similar result as ISOPAC-80 at higher doses. The sulfate based STERNPAC-70 yielded good result at higher doses but not as good as ISOPAC-80 and PASS-C.

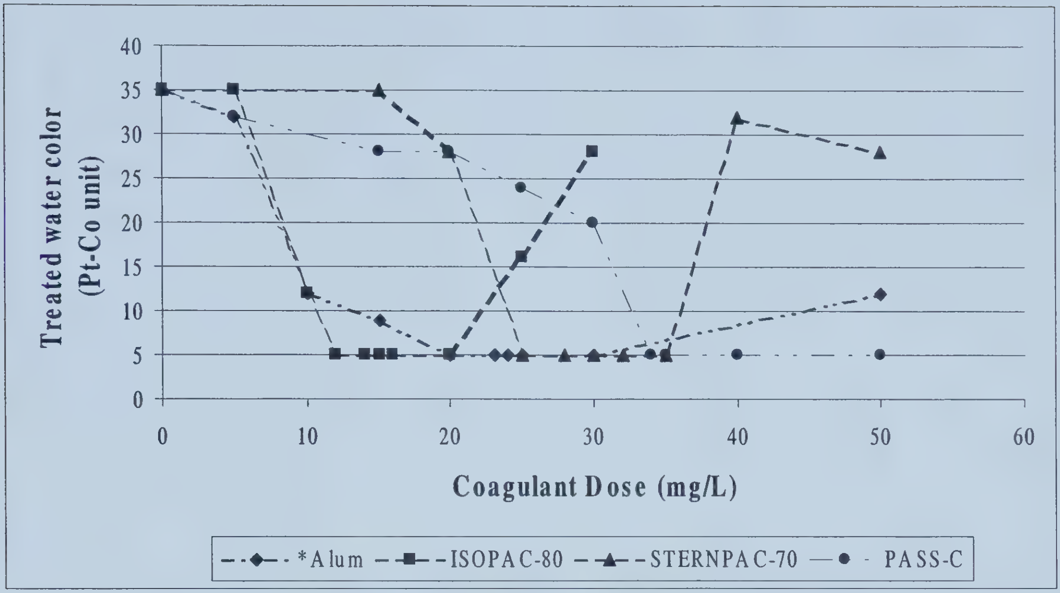

Figure B-1 Flotation performance of different coagulants for color removal in treating Port Hardy water.

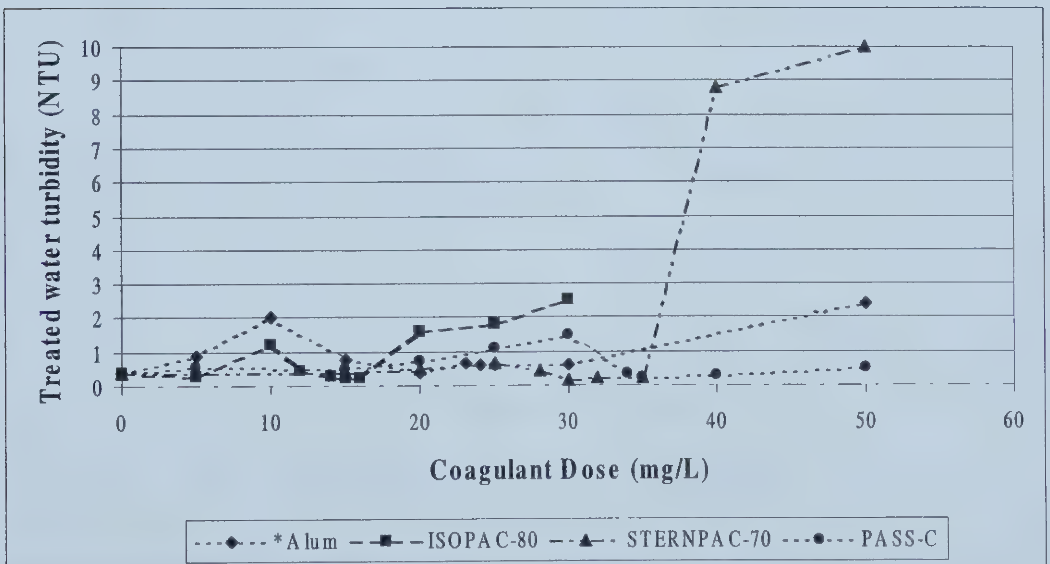

Figure B-2 Flotation performance of different coagulants for turbidity removal in treating Port Hardy water.

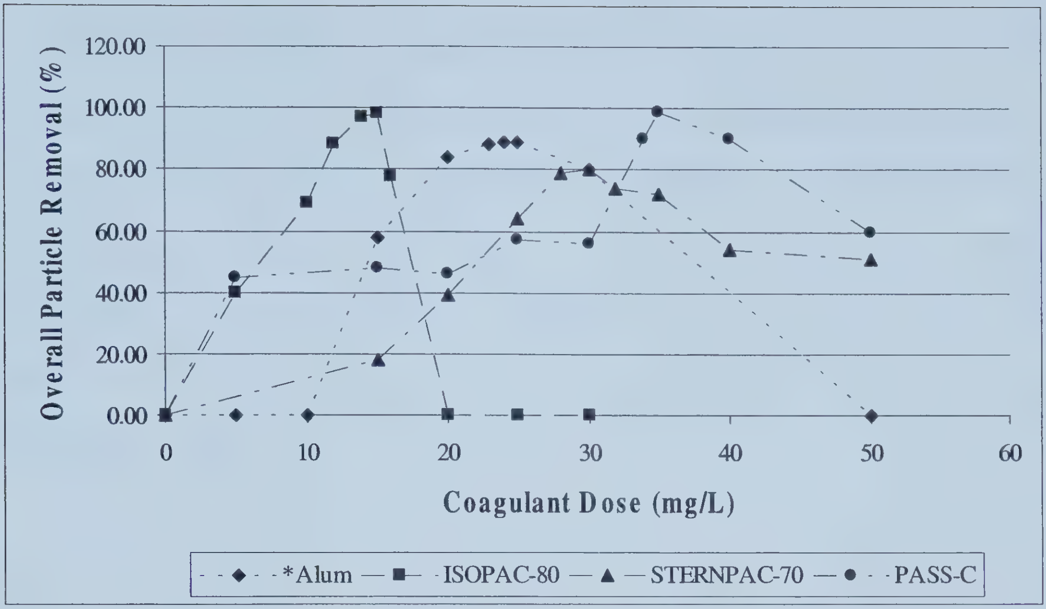

Figure B-3 Flotation performance of different coagulants for overall particle removal (%) in treating Port Hardy water.

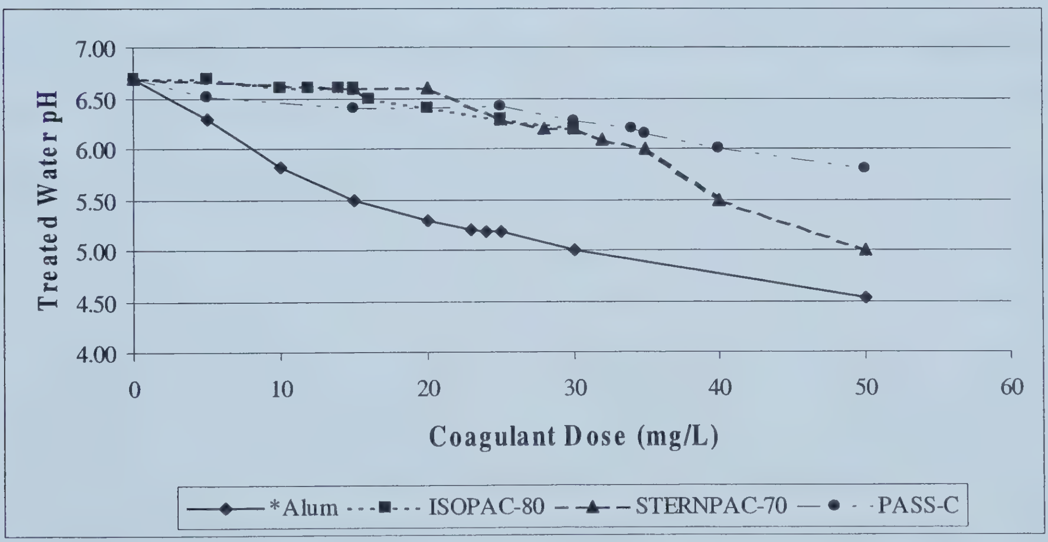

Figure B-4 Treated Water pH at different coagulants doses in treating Port Hardy water.

B.4 Conclusions

The results presented here suggest pH and turbidity control of the treated water using high basicity PACl (polyaluminum chloride) and promising practical applications in treating Port Hardy water. The benefits of this high basicity polyaluminum chloride include superior finished water quality, and reduced supplemental alkalinity requirements. The high basicity PACl is also beneficial to longer filter run lengths, reduced filter to waste cycles, lower sludge generation and lower total operating cost (Bunker et al. 1995).

B.5 Recommendations

Two critical areas warrant further research. First, these reported studies did not involve post filtration research. Secondly, the studies reported here is batch, bench-scale efforts. The true effectiveness of optimum coagulant dose can be established and further verified with pilot and eventually full-scale confirmation.